Adapting Entities across Languages and Cultures

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Abstract

How would you explain Bill Gates to a German? He is associated with founding a company in the United States, so perhaps the German founder Carl Benz could stand in for Gates in those contexts. This type of translation is called adaptation in the translation community (Vinay and Darbelnet, 1995). Until now, this task has not been done computationally. Automatic adaptation could be used in natural language processing for machine translation and indirectly for generating new question answering datasets and education. We propose two automatic methods and compare them to human results for this novel NLP task. First, a structured knowledge base adapts named entities using their shared properties. Second, vector arithmetic and orthogonal embedding mappings identify better candidates, but at the expense of interpretable features. We evaluate our methods through a new dataset[1] of human adaptations.

1 When Translation Misses the Mark

Imagine reading a translation from German, "I saw Merkel eating a Berliner from Dietsch on the ICE". This sentence is opaque without cultural context.

An extreme cultural *adaptation* for an American audience could render the sentence as "I saw Biden eating a Boston Cream from Dunkin' Donuts on the Acela", elucidating that Merkel is in a similar political post to Biden; that Dietsch (like Dunkin' Donuts) is a mid-range purveyor of baked goods; both Berliners and Boston Creams are filled, sweet pastries named after a city; and ICE and Acela are slightly ritzier high-speed trains. Human translators make this adaptation when it is appropriate to the translation (Gengshen, 2003).

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[1] Available at https://go.umd.edu/adaptation

Bill Gates		
Top Adaptations:		
WikiData	**3CosAdd**	**Human**
F. Zeppelin	congstar	A. Bechtolsheim
Günther Jauch	Alnatura	Dietmar Hopp
N. Harnoncourt	GMX	Carl Benz

Table 1: WikiData and unsupervised embeddings (**3CosAdd**) generate adaptations of an entity, such as Bill Gates. Human adaptations are gathered for evaluation. American and German entities are color coded.

Because adaptation is understudied, we leave the full translation task to future work. Instead, we focus on the task of cultural adaptation of entities: given an entity in a source, what is the corresponding entity in English? Most Americans would not recognize Christian Drosten, but the most efficient explanation to an American would be to say that he is the "German Anthony Fauci" (Loh, 2020). We provide top adaptations suggested by algorithms and humans for another American involved with the pandemic response, Bill Gates, in Table 1.

Can machines reliably find these analogs with minimal supervision? We generate these adaptations with structured knowledge bases (Section 3) and word embeddings (Section 4). We elicit human adaptations (Section 5) to evaluate whether our automatic adaptations are plausible (Section 5.3).

2 Wer ist Bill Gates?

We define cultural adaptation and motivate its application for tasks like creating culturally-centered training data for QA. Vinay and Darbelnet (1995) define adaptation as translation in which the relationship not the literal meaning between the receiver and the content needs to be recreated.

You could formulate our task as a tradi-

tional analogy Drosten::Germany as Fauci::United States (Turney, 2008; Gladkova et al., 2016), but despite this superficial resemblance (explored in Section 4), traditional approaches to analogy ignore the influence of culture and are typically *within* a language. Hence, analogies are tightly bound with culture; humans struggle with analogies outside their culture (Freedle, 2003).

We can use this task to identify named entities (Kasai et al., 2019; Arora et al., 2019; Jain et al., 2019) and for understanding other cultures (Katan and Taibi, 2004).

2.1 ... and why Bill Gates?

This task requires a list of named entities adaptable to other cultures. Our entities come from two sources: a subset of the top 500 most visited German/English Wikipedia pages and the non-official characterization list (Veale, 2016, NOC), "a source of stereotypical knowledge regarding popular culture, famous people (real and fictional) and their trade-mark qualities, behaviours and settings". Wikipedia contains a plethora of singers and actors; we filter the top 500 pages to avoid a pop culture skew.[2] We additionally select all Germans and a subset of Americans from the Veale NOC list as it is human-curated, verified, and contains a broader historical period than popular Wikipedia pages. Like other semantic relationships (Boyd-Graber et al., 2006), this is not symmetric. Thus, we adapt entities in both directions; while Berlin is the German Washington, DC, there is less consensus on what is the American Berlin, as Berlin is both the capital, a tech hub, and a film hub. A full list of our entities is provided in Appendix D.

3 Adaptation from a Knowledge Base

We first adapt entities with a knowledge base. We use WikiData (Vrandečić and Krötzsch, 2014), a structured, human-annotated representation of Wikipedia entities that is actively developed. This resource is well-suited to the task as features are standardized both within and across languages.

Many knowledge bases explicitly encode the nationality of individuals, places, and creative works. Entities in the knowledge base are a discrete sparse vector, where most dimensions are unknown or not applicable (e.g., a building does not have a spouse).

For example, Angela Merkel is a human (instance of), German (country of citizenship), politician (occupation), Rotarian (member of), Lutheran (religion), 1.65 meters tall (height), and has a PhD (academic degree). How would we find the "most similar" American adaptation to Angela Merkel? Intuitively, we should find someone whose nationality is American.

Some issues immediately present themselves; contemporary entities will have more non-zero entries than older entities. Some characteristics are more important than others: matching unique attributes like "worked as journalist" is more important than matching "is human".

Each entity in WikiData has "properties", which we can think about as the dimension of a sparse vector and "values" that those properties can take on. For example, Merkel has the properties "occupation" and "academic degree". *Values* for those properties are that her "occupation" is "politician" and her "academic degree" is a "doctorate". To match entities across cultures, we focus on matching properties rather than values; many of the values are more relevant inside a culture. For example, we cannot find American politicians who belong to the Christian Democratic Union, but we can find politicians who have an academic degree and a dissertation title.

As a toy example, if Beethoven, Merkel, and Bach all have only two *properties*: Beethoven has an "occupation" and "genre", Merkel has an "Erdős number" and "political party", and Bach has a "occupation" and "genre", then Beethoven and Bach has a distance of zero and are the closest entities while Merkel has a distance of two since {"Erdős number", "political party"} is two away from {"occupation", "genre"}.

First, we bifurcate WikiData into two sets: an American set $\mathcal{A}$ for items which contain the *value* "United States of America" and a German set $\mathcal{D}$ for those with German values.[3] This is a liberal approximation, but it successfully excludes roughly seven out of the eight million items in WikiData. Then we explore the *properties* from WikiData. We create entity vectors with dimensions corresponding to frequently-occurring properties.

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[2]We discuss the applicability of using Wikipedia (i.e., what proportion of the English Wikipedia is visited from the United States) in Appendix B.

[3]While the geopolitical definition of American is straightforward, the German nation state is more nuanced (Schulze, 1991). Following Green (2003), we adopt members of the Zollverein or the German Confederation as "German" *as well as their predecessor and successor states*. This approach is a more inclusive (Großdeutschland) definition of "German" culture.

The *properties* are discrete and categorical; Merkel either has an "occupation" or she does not. Each entity then has a sparse vector. We calculate the similarity of the vectors with Faiss's L_2 distance (Johnson et al., 2021) and for each vector in $\mathcal{A}$ find the closest vector in $\mathcal{D}$ and *vice versa*.

So who is the American Angela Merkel? One possible answer is Woodrow Wilson, a member of a "political party", who had a "doctoral advisor" and a "religion", and ended up with "awards". This answer may be unsatisfying as it was Barack Obama who sat across from Merkel for nearly a decade. To capture these more nuanced similarities, we turn to large text corpora in Section 4.

4 An Alternate Embedding Approach

While the classic NLP vector example (Mikolov et al., 2013c) isn't as magical as initially claimed (Rogers et al., 2017), it provides useful intuition. We can use the intuitions of the cliché:

$$\overrightarrow{\text{King}} - \overrightarrow{\text{Man}} + \overrightarrow{\text{Woman}} = \overrightarrow{\text{Queen}} \qquad (1)$$

to adapt between languages.

This, however, requires relevant embeddings. First, we use the entire Wikipedia in English and German, preprocessed using Moses (Koehn et al., 2007). We follow Mikolov et al. (2013b) and use named entity recognition (Honnibal et al., 2020) to tokenize entities such as Barack_Obama.

We use word2vec (Mikolov et al., 2013b), rather than FastText (Bojanowski et al., 2017), as we do not want orthography to influence the similarity of entities. Angela Merkel in English and in German have quite different neighbors, and we intend to keep it that way by preserving the distinction between languages.

However, the standard word2vec model assumes a single monolingual embedding space. We use unsupervised Vecmap (Artetxe et al., 2018), a leading tool for creating cross-lingual word embeddings, to build bilingual word embeddings. We propose two approaches for adaptation.

3CosAdd We follow the word analogy approach of 3CosAdd[4] (Levy and Goldberg, 2014; Köper et al., 2016). American→German adaptation takes the source entity's (v) embedding in the English vector space and looks for its adaptation (u^*) based on embeddings in the German space. This is like the word analogy task, i.e., what entity has the

role in the German culture as v does in American culture. As an example, Merkel has a similar role in the German culture as Biden. Formally, the adaptation of the English entity v into German is

$$\overrightarrow{a} \equiv \text{avg}\left(\overrightarrow{E^{en}}_{\text{United\_States}}, \overrightarrow{E^{de}}_{\text{USA}} \right) \qquad (2)$$

$$\overrightarrow{d} \equiv \text{avg}\left(\overrightarrow{E^{en}}_{\text{Germany}}, \overrightarrow{E^{de}}_{\text{Deutschland}} \right) \qquad (3)$$

$$u^* = \arg\max_{u \in V^{de}} \text{sim}\left(\overrightarrow{E_u^{de}}, \overrightarrow{E_v^{en}} - \overrightarrow{a} + \overrightarrow{d} \right), \quad (4)$$

where $\overrightarrow{E_w^l}$ is the embedding of word w in language l, V^{de} is the German vocabulary and sim is the cosine similarity. The American anchor word $\overrightarrow{a}$ and German anchor $\overrightarrow{d}$ represent the American and German cultures.[5] We average the English and German embeddings of the individual word types for robust anchor vectors. In standard analogies, as in Equation 1, the $\overrightarrow{a}$ and $\overrightarrow{d}$ vectors are different for each test pair; here they are the same for each example, as we always are pivoting between the two cultures.

Learned adaptation To eliminate the need for manual anchor selection for both cultures, our second approach learns the adaptation as a linear transformation of source embeddings to the target culture given a few adaptation examples. Specifically, we use the human adaptations sourced for the Wikipedia entities as training for the Veale NOC ones. We follow the work of Mikolov et al. (2013a) and learn a transformation matrix $\mathbf{W}_{en \to de}$ for American→German by minimizing the L_2 distance of $\mathbf{W}_{en \to de} \overrightarrow{E}_{v_i}^{en}$ and $\overrightarrow{E}_{u_i}^{de}$ over gold adaptation $v_i, u_{i_{i=1}}^n$ entity pairs. The adaptation of a source entity v is $u^* = \mathbf{W}_{en \to de} \overrightarrow{E}_v^{en}$. Likewise, we learn the reverse mapping $\mathbf{W}_{de \to en}$ for German→American adaptation. This requires supervised training data—but not much (Conneau et al., 2018)—which we collect in Section 5.

5 Comparing Automation to Human Judgment

The automated methods can generate entities at scale, but humans have to evaluate their relevance.

5.1 Adaptation by Locals

Since quality control is difficult for generation (Peskov et al., 2019), we need users who

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[4]We experiment with 3CosMul as well but found 3CosAdd generally more robust.

[5]USA is used to refer to the United States in German. Der Spiegel, the largest newspaper, calls their US section USA.

will answer the task accurately. We recruit five American citizens educated at American universities and five German citizens educated at German ones. These human annotations serve as a gold standard against which we can compare our automated approaches. To improve the user experience, we create an interface that provides a brief summary of each source entity from Wikipedia and asks the users to select a target adaptation that autocompletes Wikipedia page titles (all entities; targets are not limited to the lists in Section 2) in a text box *a la* answer selection in Wallace et al. (2019). The annotation task requires two hours for our users to complete. Obviously, German annotators are more familiar with German culture than the Americans, and vice-versa. Annotators translate into their native language. Since we are focusing on popular entities, they are often known despite the cultural divide, but the introductory paragraph from Wikipedia reminds users if not.

5.2 Are the Adaptations Plausible?

To validate and compare all our adaptation strategies' precision, five German translators[6] who understand American culture assess the adaptations. The top five adaptations from WikiData, 3CosAdd, learned adaptation, and humans—as well as five randomly selected options from the human pool—are evaluated for plausibility on a five-level Likert scale.[7] Fleiss' Kappa (0.382) and Krippendorf's Alpha (0.381) assess interannotator Agreement; this "fair" agreement suggests that vetting an adaptation is challenging and sometimes subjective, even for translators.

5.3 Why Adaptation is Difficult

Embedding adaptations are better than Wikidata's, and human adaptations are better still (Figure 1). Thus, we use human adaptations as the gold standard for evaluating recall. Only the learned embedding method uses training data, so we use human adaptations from Wikipedia to train the projection matrix and evaluate (for all methods) using human adaptations the NOC list. Given that the task is subjective, we take our results with a grain of salt given cultural variation (e.g., some people view Angela Merkel's conservatism as a defining characteristic, while others focus on her science pedigree).
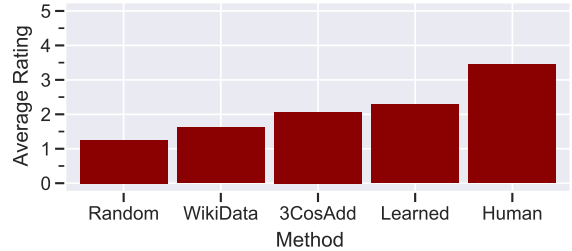

Figure 1: We validate adaptation strategies with expert translators on a five-point Likert scale. The human-generated adaptations are rated best—between "related" (3) and "similar" (4). These human adaptations become the reference for evaluation in Table 2.

Data	Metric	WikiData	3CosAdd	Learned
American→ German				
Wikipedia	Rec@5	7.5%	**14.2%**	-
	Rec@100	34.4%	**52.8%**	-
	MRR	0.05	**0.10**	-
Veale NOC	Rec@5	3.0%	22.9%	**28.6%**
	Rec@100	42.4%	**51.4%**	45.7%
	MRR	0.03	0.17	**0.24**
German→ American				
Wikipedia	Rec@5	3.1%	**17.2%**	-
	Rec@100	15.4%	**40.5%**	-
	MRR	0.01	**0.12**	-
Veale NOC	Rec@5	0.0%	**25.0%**	**25.0%**
	Rec@100	25.0%	**70.0%**	55.0%
	MRR	0.02	0.12	**0.15**

Table 2: If we consider human adaptations as correct, where do they land in the ranking of automatic adaptation candidates? In this recall-oriented approach, learned mappings (which use a small number of training pairs), rate highest.

We use the mean reciprocal rank (Voorhees, 1999, MRR) to measure how high the gold adaptations are ranked by our other adaptation strategies. Since MRR decreases geometrically and our gold standard is not exhaustive, the Recall@5, and @100 metrics are more intuitive. We calculate Recall@n by measuring what fraction of the correct adaptations of a source entity is retrieved in the top n predictions.[8] Table 2 validates that the human annotations are near the top of the automatic adaptations; the precision-oriented evaluation (Figure 1) validates whether the top of the list is reasonable. All human annotations and a sample of the automatic adaptations are provided in Appendix D.

5.4 Qualitative Analysis

There is no single answer to what makes a good adaptation. Let us return to the question of who Bill Gates is, which underlines how there is often no one right answer to this question but several context-specific possibilities. The human adaptations show the range of plausible adaptations, each appropriate for a particular facet of the position Bill Gates has in US society. As previously mentioned, Carl Benz represents a larger than life founder who created an entire industry with his company. However, Carl Benz made cars, not computers.

Even within technology, different adaptations highlight different aspects of Bill Gates. Like the implementer of the BASIC programming language, Konrad Zuse contributed to computers that were more than single-purpose machines. Just as as Bill Gates's Microsoft is seen as a stodgy tech giant, Dietmar Hopp founded SAS, a giant German tech company that is more often discussed in board rooms than in living rooms. And because the epicenter of modern tech is America's West Coast, Andreas von Bechtolsheim represents a German founder of Sun Microsystems and early Google investor that made his way to Silicon Valley.

Other times, there is more consensus: a majority of raters declare Angela Merkel is the German Hilary Clinton, and Joseph Smith is the American Martin Luther. There are even some unanimous adaptations: Bavaria is the German California. Adaptations of fictional characters seem particularly difficult, although this may represent the supremacy of American popular culture; Superman and Homer Simpson are so well known in Germany that there are no clear adaptations; Till Eulenspiegel, Maverick, Bibi Blocksberg are not superheroes from a dying world and Heidi is not a dumb, bald everyman.

6 A New Computational Task

We formally introduce entity **adaptation** as a new computational task. Word2vec embeddings and WikiData can be used to figuratively—not just literally—translate entities into a different culture. Humans are better at generating candidates for this task than our computational methods (Figure 1). These methods are well-motivated, but have room for improvement. Knowledge bases improve over time and increased coverage of entities—as well as improved information about each entity—would improve the method. Alternate word embedding approaches—perhaps those that discard orthography—may provide better candidates. Even humans occasionally disagree with other humans on this task, so evaluation for this task is nontrivial.

Our new dataset of machine-generated adaptations, human adaptations, and human evaluation of these adaptations can serve as an evaluation for future automatic methods.

People need NLP systems that reflect their language **and** culture, but datasets are lacking: adaptation can help. There has been an explosion of English-language QA datasets, but other languages continue to lag behind. Several approaches try to transfer English's bounty to other languages (Lewis et al., 2020; Artetxe et al., 2019), but most of the entities asked about in major QA datasets are American (Gor et al., 2021). Adapting entire questions will require not just adapting entities and non-entities in tandem but will also require integration with machine translation (Kim et al., 2019; Hangya and Fraser, 2019). Our automatic methods did not create precise adaptations, but the alternative "incorrect" adaptations may be useful for low-precision tasks, such as generating numerous simple open-ended questions or gauging the popularity of a entity.

Given the existence of robust datasets in high resource languages can we **adapt**, rather than literally translate, them to other cultures and languages?

7 Acknowledgments

Ethics

We worked with human participants to collect our data. They are all adults who participated of their own volition and no payment was made. No personal data was collected or used for the dataset. For evaluation of the adaptations, we hired translators through Upwork. They were paid $40 for a task that took roughly between one and two hours.

The broad motivation of this work is to spread cultural understanding. Humans must be kept in-the-loop for making claims about cultural relevance. Having multiple diverse opinions is necessary for supporting any cultural claim. Like with language, nationality is often correlated with culture, but is not synonymous. Large countries contain multitudes, while some nationalities (e.g., Kurds) lack a *de jure* nation but span many nations. We elide this detail and focus on information often available in knowledge bases.

These lists contain figures that are controversial. From a research perspective, research datasets should reflect the real world and prior work, thus we include prominent entities as identified by Veale NOC and Wikipedia. Any list may contain biases in the collection processes, and this should not be thought of as an exclusive and definitive list, but as a start that can be refined and ultimately expanded to other cultures.

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A Appendix

Our appendix contains our entire human-collected dataset, as well as a sample of our WikiData and embedding approaches for adaptation.

Figure 2 shows our collection tool. Table 3 shows German→American Veale NOC items. Table 4 shows American→German Veale NOC items. Table 5 shows German→American Veale NOC items. Table 6 shows American→German Veale NOC items.

Table 7 shows our WikiData predictions, Table 8 shows our 3CosAdd predictions. and Table 9 shows our Learned Adaptations predictions. We pose several background questions about Wikipedia and WikiData as well:

B Wikipedia Analysis

Are the Wikipedia pages in German and English visited from the associated country?   Yes; the Wikipedias for the respective languages are most used by visitors located in those countries: 63% of German wikipedia was visited from Germany and 32% of English Wikipedia was visited from the United States in the past year.[9]

Are the top Wikipedia topics notably different across languages?   Yes; less than a quarter of top 500 searches for 2019 are identical across English and German.

Does WikiData cover areas outside of the United States?   *Wikipedia* coverage does not mean that *WikiData* annotations are conducted equally across German and American entities. Analyzing WikiData[10] reveals a discrepancy in coverage of Germans and Americans.

Out of 8,126,559 titles, 1,030,762 include a reference to the United States in any capacity. However, only 184,692 contain a reference to (broader) Germany. This imbalance is significant but has enough German items for our methodology. As WikiData is a maintained resource, there is room for future additional coverage and standardization of fields.

Countries use different names throughout history. While the United States of America is straightforward, Germany includes several variations, such as: German Empire, the Kingdom of Bavaria, the Kingdom of Prussia, etc. The WikiData feature-based approach can be used for other countries as well (. . . or anything that is consistently coded). For example, there are 65,957 Russian, 152,701 French, and 48,026 Chinese items in WikiData.[11]

Are the top Wikipedia topics necessarily belonging to the culture?   No; the top 10 most visited German Wikipedia includes a cultural potpurri: Germany, Greta Thurnberg, Asperger Syndrome, Game of Thrones, and Freddie Mercury. While there are *uniquely* German entities in the longer list—ZDF, Capital Bra, The Cratez, Niki Lauda—we **cannot** conclude that all top entities in a language belong culturally to a given country. Therefore, we need a stricter methodology.

Where does one find entities?   We rely on a human-sourced dataset: Veale's Non-Official Characterization list (Veale, 2016). This list contains 1031 people, real and fictional, such as Daniel Day-Lewis, Anton Chekhov, and Bridget Jones. These people are annotated with properties, one of which is conveniently their address. There are 25 people with a German location and 575 with an American one. Removing fictional characters written by non-nationals causes the German leaves the list with 20 entities. An American author filters the list of Americans down to 35 iconic ones with achievements that span politics, music, activism, athletics, and pop culture.

Wikipedia provides another avenue for gauging popular topics in a language. We manually filter the top 500 German/English Wikipedia topics to remove non-German/non-American entities; Game of Thrones and Unix-Shell are popular in the German Wikipedia, but they are not culturally idiosyncratic. For the 2019 German Wikipedia we are left with roughly 200 items, which we further reduce down to 120

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[9]https://stats.wikimedia.org/
[10]we use a full 1.2 Terabyte dump as of 10.26.20
[11]the modern day name countries only

after putting a cap on pop culture entities. For the American counterpart, over 300 items are culturally American. We add a three-year filter to remove pop items to make it comparable to the German one.

C Interfaces

We are studying cultural differences between German and American wikipedia. These are entities that are top 500 entities from Wikpedia for the German language. Please type whichever AMERICAN entity you think is most similar to the provided German entity. If you are unfamiliar with the entity, you may reference an outside source.

The following German Entity is most similar to which American Entity:

Deutschland

Germany (German: Deutschland, German pronunciation: [ˈdɔʏtʃlant]), officially the Federal Republic of Germany (German: Bundesrepublik Deutschland, listen), is a country in Central and Western Europe. Covering an area of 357,022 square kilometres (137,847 sq mi), it lies between the Baltic and North seas to the north, and the Alps to the south. It borders Denmark to the north, Poland and the Czech Republic to the east, Austria and Switzerland to the south, and France, Luxembourg, Belgium and the Netherlands to the west. Various Germanic tribes have inhabited the northern parts of modern Germany since classical antiquity. A region named Germania was documented before AD 100.

United | Submit

United
United States
United Kingdom
United States Electoral College
United States Senate
United States House of Representatives
United States presidential election
United States Congress
United Arab Emirates
United Nations

Examples:
Michael Schumaher: Michael Jordan
Why? Both most famous athletes.

Berlin: Washington D.C.
Why? Both are capitals.

Angela Merkel: ?
It could be Donald Trump if you think the current presid... ...looking at political views. Or Hillary Clinton to preserve gender and political importa...

*This may not be symmetrical. Berlin may be the Germa... ...merican Berlin.
*You can propose the same analogy for multiple entities... ...Washington D.C. in your opinion (as the capital or as the cultural hub of the count...
*Bad analogies are based on literal names: Michael Schumacher is not similar to Michael Bay just because their names are Michael, and not Shoemaker just because it is a translation or how it sounds.

Figure 2: Our interface provides users with information about the entity and asks them to select an option from possible Wikipedia pages

Compare the below German entities to this American entity: **Abraham Lincoln** / Abraham Lincoln was an American statesman and lawyer who served as the 16th president of the United States from 1861 until his assassination in 1865.

Click for Instructions

	Unrelated	Slightly Related	Somewhat Related	Somewhat Similar	Very Similar
Konrad Adenauer / Konrad Hermann Joseph Adenauer was a German statesman who served as the first Chancellor of the Federal Republic of Germany from 1949 to 1963.	○	○	○	○	○
Helmut Schmidt / Helmut Heinrich Waldemar Schmidt was a German politician and member of the Social Democratic Party of Germany , who served as Chancellor of the Federal Republic of Germany from 1974 to 1982.	○	○	○	○	○
Willy Brandt / Willy Brandt was a German politician and statesman who was leader of the Social Democratic Party of Germany from 1964 to 1987 and served as Chancellor of the Federal Republic of Germany from 1969 to 1974.	○	○	○	○	○
Helmut Kohl / Helmut Josef Michael Kohl was a German statesman and politician of the Christian Democratic Union who served as Chancellor of Germany from 1982 to 1998 and as chairman of the CDU from 1973 to 1998.	○	○	○	○	○

Figure 3: Our Qualtrics survey

D Data

Entity	Human Adaptation: NOC German→American
Adolf Eichmann	Andrew Jackson, Andrew Jackson, Franklin D. Roosevelt, Nathan Bedford Forrest, Steve Bannon
Angela Merkel	Barack Obama, Donald Trump, Hillary Clinton, Hillary Clinton, Hillary Clinton, Hillary Clinton, Joe Biden
Baron Munchausen	Captain America, Daniel Bolger, Joseph Smith, Paul Bunyan, Robert Jordan , Yankee Doodle
Carl von Clausewitz	Alfred Thayer Mahan, Dwight D. Eisenhower, Henry Knox, Robert E. Lee, Ulysses S. Grant
Friedrich Nietzsche	Ayn Rand, Henry David Thoreau, Henry Thoreau, Jordan Peterson, William James
Henry Kissinger	Henry Kissinger, Henry Kissinger, John Kerry, Madeleine Albright, Richard Nixon
Immanuel Kant	Benjamin Franklin, John Dewey, John Locke, John Rawls, Robert Nozick
Johann Sebastian Bach	Aaron Copland, Elvis Presley, Elvis Presley, Irving Berlin, Johnny Cash, Scott Joplin
Johann Wolfgang von Goethe	Edgar Allan Poe, Ernest Hemingway, Walt Whitman
Johannes Gutenberg	Benjamin Franklin, Bill Gates, Eli Whitney, Thomas Edison
Joseph Goebbels	David Duke, Franklin D. Roosevelt, George Rockwell, Rupert Murdoch, david duke
Karl Lagerfeld	Anna Wintour, Anna Wintour, Marc Jacobs, Ralph Lauren, Ralph Lauren, Ralph Lauren, Ralph Lauren
Karl Marx	Angela Davis, Beck, Bernie Sanders, John Jay, John Rawls, John Rawls
Leni Riefenstahl	DW Griffeth, David Wark Griffith, Frank Capra, Judy Garland
Ludwig van Beethoven	Aaron Copland, Aaron Copland, Aaron Copland, Elvis Presley, Frank Sinatra, George Gershwin, George Gershwin, Scott Joplin
Marlene Dietrich	Bette Davis, Clara Bow, Elizabeth Taylor, Marilyn Monroe, William Tecumseh Sherman
Martin Luther	Barry Goldwater, Brigham Young, Joseph Smith, Joseph Smith, Joseph Smith
Otto von Bismarck	Abraham Lincoln, George Washington, George Washington, George Washington, George Washington, Ulysses S. Grant
Pope Benedict XVI	Billy Graham, Billy Graham, Brigham Young, John Carroll , Seán Patrick O'Malley
Richard Wagner	Charles Ives, Frank Sinatra, Leonard Bernstein, Philip Glass

Table 3: Veale NOC German→American adaptations.

Entity	Human Adaptation: NOC American→German adaptations
Abraham Lincoln	Helmut Kohl, Konrad Adenauer, Wilhelm Friedrich Ludwig von Preußen, Willy Brandt, Willy Brandt
Al Capone	Adolf Leib, Carlos Lehder-Rivas, Jan Marsalek, Nasser Abou-Chaker, Nasser About-Chaker
Alfred Hitchcock	Bernd Eichinger, Bernd Eichinger, Michael Bully Herbig, Roland Emmerich, Wim Wenders
Benedict Arnold	Hansjoachim Tiedge, Otto von Bismarck, Otto von Bismarck, Robert Blum
Bill Gates	Andreas von Bechtolsheim, Carl Benz, Dietmar Hopp, Konrad Zuse
Britney Spears	Helene Fischer, Herbert Grönemeyer, Jeanette Biedermann, Nena, Til Schweiger
Charles Lindbergh	Ferdinand von Richthofen, Heinrich Horstman, Karl Wilhelm Otto Lilienthal, Ludwig Hofmann, Wernher von Braun
Donald Trump	Adolf Hitler, Adolf Hitler, Carsten Maschmeyer, Christian Lindner
Elvis Presley	Peter Kraus, Rammstein, The Scorpions, Udo Lindenberg, Udo Lindenberg
Ernest Hemingway	Günter Grass, Hermann Hesse, Johann Wolfgang von Goethe, Karl May, Martin Walser
Frank Lloyd Wright	Gerhard Richter, Hugo Häring, Karl Lagerfeld, Max Dudler, Walter Gropius
George Washington	Friedrich II, Heinrich I, Konrad Adenauer, Otto I. der Große, Otto von Bismarck
Henry Ford	Carl Benz, Carl Benz, Carl Benz, Ferdinand Porsche, Gottlieb Wilhelm Daimler
Hillary Clinton	Angela Merkel, Angela Merkel, Angela Merkel, Kramp-Karrenbauer, Sahra Wagenknecht
Homer Simpson	Alf, Heidi, Pumuckl, Werner, Werner - Beinhart!
Jack The Ripper	Armin Meiwes, Der Bulle von Tölz, Joachim Kroll, Karl Denke, Rudolf Pleil
Jay Z	Capital Bra, Marteria, Sido, Sido, Sido
Jimi Hendrix	Bela B., Gisbert zu Knyphausen, Herbert Grönemeyer, Rudolf Schenker, Spider Murphy Gang
John F. Kennedy	Hanns Martin Schleyer, Willy Brandt, Willy Brandt, Wolfgang Schäuble
Kim Kardashian	Carmen Geiss, Gina-Lisa Lohfink, Heidi Klum, Heidi Klum, Sarah Connor
Louis Armstrong	Günter Sommer, Helmut Brandt, Jan Delay, Michael Abene, Mozart
Marilyn Monroe	Heidi Klum, Ingrid Steeger, Marlene Dietrich, Micaela Schäfer, Uschi Glas
Michael Jordan	Dirk Nowitzki, Dirk Nowitzki, Dirk Nowitzki, Franz Beckenbauer, Michael Schuhmacher
Neil Armstrong	Alexander Gerst, Sigmund Jähn, Sigmund Jähn, Ulf Merbold, Wernher von Braun
Noam Chomsky	Helmut Glück, Juergen Habermas, Jürgen Habermas, Ludwig Wittgenstein, Wilhelm Röntgen
Oprah Winfrey	Anne Will, Arabella Kiesbauer, Maybrit Illner, Thomas Gottschalk, Thomas Gottschalk

Orville Wright	Carl Benz, Gustav Otto, Gustav Weißkopf, Otto Lilienthal, Werner von Braun
Richard Nixon	Franz Josef Strauss, Helmut Kohl, Ludwig Erhard, Ludwig Erhard, Richard von Weizsäcker
Rosa Parks	Anne Wizorek, Marie Juchacz, Sophie Scholl, Sophie Scholl, Vera Lengsfeld
Serena Williams	Andrea Petkovic, Boris Becker, Sabine Lisicki, Steffi Graf, boris becker
Steve Jobs	Carl Benz, Dietmar Hopp, Dietmar Hopp, Karl Lagerfeld
Steven Spielberg	Michael Bully Herbig, Roland Emmerich, Roland Emmerich, Roland Emmerich, Wim Wenders
Superman	Bibi Blocksberg, Fix and Foxi, Maverick, Superman, Till Eulenspiegel
Tiger Woods	Boris Becker, Martin Kaymer, Martin Kaymer, Michael Schumacher, Serge Gnabry
Walt Disney	Axel Springer, Christian Becker, Franz Mack, Gerhard Hahn, Rötger Feldmann

Table 4: Veale NOC American→German adaptations.

Entity	Human Adaptation: Wikipedia German→American
ARD	NPR, PBS, PBS
Adolf Hitler	Donald Trump, Donald Trump, Franklin D. Roosevelt, Franklin D. Roosevelt, Franklin D. Roosevelt
Airbus	Boeing, Boeing, Boeing, Boeing, Lockheed Martin
Albert Einstein	Carl Sagan, J. Robert Oppenheimer, J. Robert Oppenheimer, John Forbes Nash Jr., Thomas Edison
Alice Merton	Ariana Grande, Elle King, K.T. Tunstall, P!NK, Vanessa Carlton
Alternative für Deutschland	Libertarian Party , Republican Party, Tea Party movement
Andrea Nahles	Elizabeth Warren, Hillary Clinton, Nancy Pelosi, Tammy Duckworth
Andrej Mangold	Kawhi Leonard, Kevin Durant, Kris Humphries, Yao Ming
Annalena Baerbock	Al Gore, Al Gore, Alexandria Ocasio-Cortez, Bernie Sanders, Jill Stein
Anne Frank	Anna Green Winslow, Clara Barton, Emmett Till, Kunta Kinte
Annegret Kramp-Karrenbauer	Condoleezza Rice, Hillary Clinton
AnnenMayKantereit	Guns N' Roses, Milky Chance, Polar Bear Club, Red Hot Chili Peppers
Apache 207	Fetty Wap, Tekashi 69, XXXTentacion, Zayn Malik
Arnold Schwarzenegger	Chuck Norris, Dwayne Johnson, Ronnie Coleman, Sylvester Stallone, Sylvester Stallone
BMW	Cadillac, Cadillac, Chevrolet, Chrysler
Babylon Berlin	Game of Thrones, Man From U.N.C.L.E., Peaky Blinders , The Americans, Turn
Baden-Württemberg	California, Chicago metropolitan area, San Diego, Southern United States, Texas
Bastian Yotta	Chad Johnson, Colton Underwood, Dan Bilzerian
Bauhaus	Frank Lloyd Wright
Bayerischer Rundfunk	NPR, National Public Radio, National Public Radio, national public ra
Bayern	Florida, New York, The Confederacy
Benjamin Piwko	Bruce Lee, Colton Underwood, Derek Hough
Berlin	New York City, Portland Oregon, Washington D.C., Washington D.C., Washington D.C.
Berliner Mauer	Border Patrol Police, Mason–Dixon line, Mason–Dixon line, US-Mexican border
Bertolt Brecht	Tennessee Williams, Tennessee Williams
Björn Höcke	Lindsey Graham, Mike Pence
Borussia Dortmund	Golden State Warriors, New England Patriots, New England Patriots
Brandenburg	Maryland, New York, Northeastern United States, Richmond Virginia, Virginia
Bruno Ganz	Clint Eastwood, Ethan Hawke, Marlon Brando, Robert De Niro, Robert De Niro
Bundespräsident	First Lady, President of the United States, Speaker of the House
Bundeswehr	Department of Defense , US military, United States Armed Forces, United States Army
Capital Bra	Drake, Eminem, Eminem, Kanye West, Kendrick Lamar
Carola Rackete	American Civil Liberties Union, Dawn Wooten, Rosa Parks, Whale Wars
Carolin Kebekus	Amy Schumer, Sarah Silverman, Tina Fey, Tina Fey

Charité	Call the Midwife, Grey's Anatomy, Grey's Anatomy, The Queen's Gambit
Chris Töpperwien	Gordon Ramsey , Guy Fieri, Jeff Probst
Christoph Waltz	Anthony Hopkins, Christoph Waltz, Denzel Washington
Dark	Stranger Things, Stranger Things
Deutsche Bahn	Amtrack, Norfolk Southern Railway, Union Pacific Corporation
Deutsche Demokratische Republik	Confederate States of America, Confederate States of America, Texas, The Confederacy, The Confederate States of America
Deutsche Nationalhymne	Born in the U.S.A., Lazy Eye , Star Spangled Banner, The Star Spangled Banner
Deutschland	America, America, Continental United States, USA, United States, United States
Dieter Bohlen	Billy Joel, Blake Shelton, Daryl Hall, Paula Abdul, Ryan Seacrest
Dirk Nowitzki	LeBron James, Michael Jordan, Shaquille O'Neal
Doreen Dietel	Jessica Alba, Lisa Kudrow, Warrick Brown
Dreißigjähriger Krieg	American Civil War, American Civil War, American Indian Wars, Civil war
Elisabeth von Österreich-Ungarn	Edith Roosevelt, Hillary Clinton, Jackie Kennedy
Elyas M'Barek	Adam Sandler, Adam Sandler, Chris Pine
Europawahl in Deutschland 2019	2018 United States elections, American presidential election 2020, Us election 2018
Europäisches Parlament	North Atlantic Council, Representative of the United States of America to the European Union, United Nations, United States Congress
Evelyn Burdecki	Hannah Brown, Kaitlyn Bristowe, Kim Kardashian, Kim Kardashian
FC Bayern München	Dallas Cowboys, Dc United, New York Yankees, New York Yankees, New York Yankees
Falco	David Bowie, Frederick William Schneider III, MC Hammer, Michael Jackson
Ferdinand Sauerbruch	Ben Carson, Ben Carson, Cornelius P. Rhoads, Jonas Salk, Virginia Apgar
Flughafen Berlin Brandenburg	Cincinnati Subway, DCA , John F. Kennedy International Airport, LaGuardia Airport
Frankfurt am Main	Chicago, Los Angeles, Los Angeles, New York City, Washington D.C.
Fritz Honka	Ted Bundy, Ted Bundy, Ted Bundy, Zodiac
Hamburg	Chicago, Chicago, Los Angeles, New York, Philadelphia
Hannelore Elsner	Elizabeth Taylor, Jane Lynch, Julia Roberts
Heidi Klum	Chrissy Teigen, Cindy Crawford, Gigi Hadid, Karlie Kloss, Tyra Banks
Heinz-Christian Strache	Anthony Weiner, Ben Carson, Donald J. Trump, Rob Ford, Roger Stone
Helene Fischer	Beyoncé, Kelly Clarkson, Taylor Swift, Taylor Swift
Hessen	Arizona, Illinois, Mid-Atlantic , Napa County California
Holocaust	Chattel Slavery, Japanese interned in American camps, Slavery in the United States
Ich bin ein Star – Holt mich hier raus!	Survivor, Survivor
Jürgen Klopp	Bill Belichick, Bill Belichick, John Wooden
Kevin Kühnert	Bernie Sanders, Bernie Sanders, Bernie Sanders, Pete Buttigieg

Klaus Kinski	Christopher Lee, Clark Gable, John Wayne, Robert Pattinson, Robert Pattinson
Kontra K	50 Cent, Eminem, Eminem, Jesus Is King, Travis Scott
Köln	Boston, Chicago, Chicago, Houston
Leila Lowfire	Paris Hilton, Sasha Grey, Zendaya
Leipzig	Denver, Detroit, Miami, San Diego
Lena Meyer-Landrut	Ariana Grande, Kelly Clarkson, Kelly Clarkson, Meghan Trainor, Selena Gomez
Liechtenstein	Connecticut, Mexico, Philippines, Victoria British Columbia
Lisa Martinek	Julie Benz, Katherine Heigl, Mandy Moore, Meryl Streep
Ludwig van Beethoven	Aaron Copland, Aaron Copland, Aaron Copland, Aaron Copland, Elvis Presley, Frank Sinatra, George Gershwin, George Gershwin, Scott Joplin
Lufthansa	Delta, United, United Airlines, United Airlines
Luxemburg	Canada, Connecticut, Mexico, Victoria British Columbia
Mark Forster	Bruno Mars, Post Malone
Mero	DaBaby, Fetty Wap, Lil Nas X, Lil Nas X, Post Malone
Michael Schumacher	Dale Earnhardt, Dale Earnhardt, James Gordon, Jeff Gordon, Tiger Woods
München	Chicago, Los Angeles, New York City, New York City, Washington D.C.
Nico Santos	Harry Styles, Justin Bieber, Shawn Mendes
Niki Lauda	Dale Earnhardt, Dale Earnhardt Jr., Jeff Gordon, Jeff Gordon, Tiger Woods
Norddeutscher Rundfunk	NPR, NPR, National Public Radio, PBS, Sirius XM
Nordrhein-Westfalen	California, California
Philipp Amthor	Alexandria Ocasio-Cortez, Ben Shapiro
RAF Camora	Bad Bunny, Drake, Drake , Eminem, Future
Rammstein	Green Day, Metallica, Metallica, Metallica, Sum 41
Rhein	Mississippi, Mississippi River, Mississippi River
Robert Habeck	Al Gore, Bernie Sanders, Jill Stein, Ralph Nader
Rudi Assauer	Dave Roberts, Gregg Berhalter, Tom Flores, Vince Lombardi, Vince Lombardi
Sahra Wagenknecht	Alexandria Ocasio-Cortez, Elizabeth Warren, Elizabeth Warren, Elizabeth Warren, Nancy Pelosi
Sarah Connor	Beyoncé, Britney Spears, Mariah Carey
Schweiz	Canada, Canada, Iowa, Mexico, United States
Sebastian Kurz	Alexandria Ocasio-Cortez, Greg Abbott, Justin Trudeau, Justin Trudeau, Mitch McConnell
Serge Gnabry	Clint Dempsey, JuJu Smith-Schuster, Phillip Rivers, Stephen Curry, Zion Williamson
Sido	Eminem, Eminem, Macklemore
The Cratez	DJ Khaled, Drake , Twenty One Pilots
Thüringen	Iowa, Midwestern United States, Tennessee, Tennessee
Till Lindemann	James Hetfield, James Hetfield, James Hetfield, Ozzy Osbourne
Tom Kaulitz	Adam Levine, Blink-182, Chris Martin, Green Day, Maroon 5
UEFA Champions League	Major League Soccer, NFC, NFL, National Football League, Ncaa
Udo Jürgens	Aretha Franklin, Billy Joel, Elton John, Michael Jackson, Rolling Stone, Tom Lehrer
Udo Lindenberg	Johnny Cash, Mick Jagger, Roger Taylor , Travis Barker

Ursula von der Leyen	Condoleezza Rice, Hillary Clinton, Mike Pence, Sarah Palin, Susan Rice
Volkswagen AG	Ford Motor Company, Ford Motor Company, Ford Motor Company, Ford Motor Company, Ford Motor Company
Walter Lübcke	Harvey Milk, John F. Kennedy, John Roll, Steve Scalise
Weimarer Republik	America, Confederation Period, Congress of the Confederation, Counterculture of the 1960s, The Confederate States of America
Westdeutscher Rundfunk Köln	ABC News, NBC, NPR
Wien	Austin Texas, Richmond Virginia, Toronto, Washington D.C.
Wilhelm II.	William Howard Taft, Woodrow Wilson, Woodrow Wilson
Wolfgang Amadeus Mozart	Alan Menken, Elvis Presley, Leonard Bernstein
ZDF	NPR, NPR, National Public Radio, PBS, PBS
Österreich	Canada, Mexico, Texas, Texas, United States
Ötzi	Spirit Cave mummy, Spirit Cave mummy, Spirit Cave mummy, Sue

Table 5: Top Wikipedia German→American adaptations.

Entity	Human Adaptation: Wikipedia American→German
13 Reasons Why	Club der roten Bänder, Gute Zeiten schlechte Zeiten, Lammbock, Türkisch für Anfänger
Albert Einstein	Albert Einstein, Albert Einstein, Albert Einstein, Max Planck, Max Planck
Alexander Hamilton	Konrad Adenauer, Max Weber, Otto von Bismarck, Otto von Bismarck
American Civil War	Deutscher Krieg, Dreißigjähriger Krieg, German Revolution of 1918–1919, German revolutions of 1848–1849
American Horror Story	Dark, Der goldene Handschuh, Good Bye Lenin!, Tintenherz
Angelina Jolie	Barbara Schöneberger, Franka Potente, Marlene Dietrich, Romy Schneider, Veronica Maria Cäcilia Ferres
Apple Inc.	BMW, Fujitsu, SAP, Siemens
Ariana Grande	Lena Meyer-Landrut, Lena Meyer-Landrut, Lena Meyer-Landrut, Sarah Connor, Sarah Connor
Arnold Schwarzenegger	Arnold Schwarzenegger, Karl Lauterbach, Matthias Steiner, Peter Maffay, Ralf Rudolf Möller
Ashton Kutcher	Florian David Fitz, Matthias Schweighöfer, Til Schweiger, Til Schweiger
Australia	Australia, Russia, Schweiz, South Africa, Österreich
Avengers Infinity War	Das Arche Noah Prinzip, Fack ju Göhte, Fantastic Four, Who Am I
Barack Obama	Angela Merkel, Angela Merkel, Angela Merkel, Helmut Schmidt, Helmut Schmidt
Beyoncé	Helene Fischer, Sarah Connor, Veronica Ferres, Xavier Naidoo, Yvonne Catterfeld
Black Mirror	Dark, Dark, Die kommenden Tage, Krabat
Blake Lively	Josefine Preuß, Maria Furtwängler, Maria Furtwängler, Til Schweiger
Brad Pitt	Florian David Fitz, Frederick Lau, Til Schweiger, Til Schweiger, Til Schweiger
Bruce Lee	Götz Georg, Henry Maske, Julian Jacobi, Max Schmeling, no one is like Bruce Lee
Caitlyn Jenner	Kristin Otto, Magdalena Neuner, Magdalena Neuner, Niklas Kaul, Ulrike Meyfarth
California	Bavaria, Bavaria, Bayern, Bayern
Camila Cabello	Helene Fischer, Lena Meyer-Landrut, Lena Meyer-Landrut, Nadja Benaissa
Canada	Austria, Italy, Schweiz, Sweden, Österreich
Cardi B	Ace Tee, Pamela Reif, Sabrina Setlur, Sarah Connor, Schwester Ewa
Charles Manson	Andreas Baader, Issa Rammo, Papst benedikt xvi, Paul Schäfer
Charlize Theron	Baran bo Odar, Josefine Preuß, Josefine Preuß, Veronica Ferres, Veronica Maria Cäcilia Ferres
Cher	Marlene Dietrich, Nena, Nena, Nena
Chris Pratt	Elyas M'Barek, Jan Josef Liefers, Matthias Schweighöfer, Ralf Moeller, Til Schweiger
Clint Eastwood	Heinz Erhardt, Klaus Kinski, Mario Adorf, Til Schweiger, Wim Wenders
Darth Vader	Adolf Hitler, Belzebub, Hagen von Tronje, Jens Maul
Donald Glover	Elyas M'Barek, Helge Schneider, Money Boy, Stefan Raab

Drake	Bushido, Cro, Falco, Fler
Dwayne Johnson	Alexander Wolfe, Arnold Schwarzenegger, Peter Alexander, Tim Wiese, Tim Wiese
Elon Musk	Alexander Samwer, August Horch, Carl Benz, Herbert Diess, Werner von Siemens
Eminem	Bushido, Kollegah, Sido, Sido, Sido
Facebook	Das Erste, Lokalisten, Lokalisten, Schüler VZ, StudiVZ, StudiVZ
Friends	Gute Zeiten schlechte Zeiten, Gzsz, Lindenstraße, Stromberg
Game of Thrones	Babylon Berlin, Babylon Berlin, Babylon Berlin, Die unendliche Geschichte, Krabat
Google	Ecosia, Fastbot, SAP, SAP, i.d.k.
Harry Potter	Die Unendliche Geschichte, Die unendliche Geschichte, Harry Potter und ein Stein, Meggie Folchart
Heath Ledger	Christoph Waltz, Florian David Fitz, Henry Blanke, Matthias Schweighöfer, Tilman Valentin Schweiger
It	Dark, Der goldene Handschuh, Die Wolke, Pandorum
Jason Momoa	Arnold Schwarzenegger, Benno Fürmann, Christoph Waltz, Elyas M'Barek, Elyas M'Barek, Elyas M'Barek
Jeff Bezos	Alexander Samwer, Beate Heister, Martin Winterkorn, Oliver Samwer
Jeffrey Dahmer	Armin Meiwes, Fritz Haarmann, Joachim Kroll, Karl Denke, Karl Denke
Jennifer Aniston	Barbara Schöneberger, Diane Kruger, Diane Kruger, Franka Potente, Iris Berben
Jennifer Lawrence	Iris Berben, Josefine Preuß, Karoline Herfurth, Ruby O. Fee
Jennifer Lopez	Heidi Klum, Helene Fischer, Jeanette Biedermann, Mandy Capristo, Sarah Connor
John Cena	Arnold Schwarzenegger, Max Schmeling, Max Schmeling, Ralf Möller
Johnny Cash	Fantastischen vier, Helge Schneider, Peter Maffay, Peter Maffay
Johnny Depp	Christoph Maria Herbst, Christoph Waltz, Cro, Til Schweiger, Xavier Naidoo
Julia Roberts	Karoline Herfurth, Maria Furtwängler, Marlene Dietrich, Marlene Dietrich
Justin Bieber	Cro, Felix Jaehn, Lukas Rieger, McFittie, Mike Singer
Keanu Reeves	Daniel Brühl, Mario Adorf, Til Schweiger, til schweiger
Kylie Jenner	Barbara Schöneberger, Heidi Klum, Karoline Einhoff, Sarah Connor, Stefanie Giesinger
Lady Gaga	Helene Fischer, Nena, Nena, Nina Hagen, Sarah Lombardi
LeBron James	Dirk Nowitzki, Dirk Nowitzki, Dirk Nowitzki, Dirk Nowitzki, Toni Kroos
Leonardo DiCaprio	Matthias Schweighöfer, Moritz Bleibtreu, Til Schweiger, Til Schweiger, Til Schweiger
Lisa Bonet	Franka Potente, Iris Berben, Karoline Herfurth, Maria Furtwängler
Madonna	Blümchen, Helene Fischer, Helene Fischer, Helene Fischer, Sarah Connor
Mark Wahlberg	Florian David Fitz, Til Schweiger, Tilman Valentin Schweiger, Alexei Alexejewitsch
Martin Luther King Jr.	Hans Scholl, Hans Scholl, Helmut Palmer, Robert Blum, Sophie Scholl

Marvel Cinematic Universe	Bavaria Film, Havelstudios, Phantásien, Rat Pack Filmproduktion, Tatort
Michael Jackson	Herbert Grönemeyer, Nena, Udo Jürgens, Xavier Naidoo, Xavier Naidoo
Mila Kunis	Josefine Preuß, Matthias Schweighöfer, Vanessa Mai
Miley Cyrus	Lena Meyer-Landrut, Lukas Rieger, Nena, Sarah Connor, Yvonne Catterfeld
Muhammad Ali	Alexander Abraham, Boris Becker, Max Schmeling, Max Schmeling, Sven Ottke
Natalie Portman	Barbara Schöneberger, Diane Kruger, Franka Potente, Iris Berben
New York City	Berlin, Berlin, Berlin, Berlin, Frankfurt
Nicole Kidman	Evelyn Hamann, Franka Potente, Senta Berger, iris berben
Peaky Blinders	Dark, Dieter Schwarz, Im Westen Nichts Neues, Tatort, Tatort
Philippines	Greece, Griechenland, Mallorca, Mallorca
Post Malone	Bushido, Bushido, Cro, Cro, Kollegah
Rihanna	Helene Fischer, Lena Meyer-Landrut, Lena Meyer-Landrut, Nena
Riverdale	Babylon Berlin, Berlin Tag und Nacht, Neues vom Süderhof, Türkisch für Anfänger
Robert Downey Jr.	Christoph Waltz, Günter Strack, Martin Semmelrogge, Moritz Bleibtreu, Til Schweiger
Robin Williams	Hape Kerkeling, Heinz Erhardt, Peter Maffay, Silvia Seidel, Tim Bendzko
Ronald Reagan	Helmut Schmidt, Konrad Adenauer, Konrad Adenauer, Konrad Adenauer
Ryan Reynolds	Daniel Brühl, Florian David Fitz, Matthias Schweighöfer, Til Schweiger, Til Schweiger
Scarlett Johansson	Lena Gercke, Romy Schneider, Sarah Connor, Sarah Connor, Veronica Ferres
Selena Gomez	Lena Meyer-Landrut, Lena Meyer-Landrut, Nena, Nora Tschirner
September 11 attacks	Anschlag im OEZ, Dresden Bombing, Mauerfall, RAF-Attentate, Terroranschlag Olympia 1972
Shaquille O'Neal	Dirk Nowitzki, Dirk Nowitzki, Mehmet Scholl, Niklas Süle
Star Wars	Dark, Metropolis, Traumschiff Surprise – Periode 1, Who Am I?, i.d.k
Stephen Curry	Dirk Nowitzki, Dirk Nowitzki, Dirk Nowitzki, Dirk Nowitzki, Manuel Neuer
Stranger Things	8 Tage, Babylon Berlin, Dark, Tatort, Tatort
Sylvester Stallone	Henry Blanke, Jan Josef Liefers, Michael Bully Herbig, Michael Fassbender, Til Schweiger
Taylor Swift	Lena Meyer-Landrut, Lena Meyer-Landrut, Sarah Connor, Sarah Connor, Yvonne Catterfeld
Ted Bundy	Joachim Kroll, Josef Fritzl, Niels Högel, Rudolf Pleil, Rudolf Pleil
The Big Bang Theory	Doctor's Diary, Stromberg, Stromberg, der Tatortreiniger
The Crown	Babylon Berlin, Deutschland 83, Die Deutschen, Karl der Große
The Handmaid's Tale	Dark, Dark, Der Pass, Die Wanderhure, Er ist wieder da
The Walking Dead	Dark, Dark, Der goldene Handschuh, Zombies From Outer Space
Tom Brady	Franz Beckenbauer, Michael Ballack, Oliver Kahn, Thomas Müller, Uli Stein
Tom Cruise	Benno Fürmann, Benno Fürmann, Christoph Waltz, Elyas M'Barek, Matthias Schweighöfer
Tom Hanks	Christoph Waltz, Christoph Waltz, Daniel Brühl, Til Schweiger

Tom Hardy	Bruno Ganz, Michael Herbig, Til Schweiger, Wotan Wilke Möhring
Tom Holland	Daniel Brühl, Frederick Lau, Matthias Schweighöfer, Matthias Schweighöfer, Til Schweiger
Tupac Shakur	Farid Bang, Haftbefehl, Kollegah, Kristoffer Klauß, Peter Fox
United States	BRD, Bundesrepublik Deutschland, Deutschland, Germany, Germany
Vietnam War	Berlin Wall, First world war, Kosovokrieg, World War II
Wikipedia	Brockhaus, Brockhaus Enzyklopädie, Brockhaus Enzyklopädie, Duden, dict.cc
Will Smith	Daniel Brühl, Elyas M'Barek, Sascha Reimann, Sido, Til Schweiger
X-Men	Abwärts, Fantastic Four, Freaks, Krabat, Who Am I
YouTube	Lokalisten, MyVideo, MyVideo, ProSieben, lokalisten
Zac Efron	Frederick Lau, Lukas Rieger, Peter Kraus, Walter Sedlmayr
Zendaya	Franka Potente, Iris Berben, Lena Meyer-Landrut, Lena Meyer-Landrut, Yvonne Catterfeld

Table 6: Top Wikipedia American→German adaptations.

Entity	Top Five WikiData Adaptations
Abraham Lincoln	Victor Adler, Johann Joachim Christoph Bode, Willem Barentsz, Hermann Wagener, Robert von Mohl
Al Capone	Hans H. Zerlett, Fritz Thyssen, Adam Rainer, Franz Winkelmeier, Christian Louis, Duke of Brunswick-Lüneburg
Alfred Hitchcock	Edgar Reitz, Jan Josef Liefers, Mario Adorf, Max Frisch, Armin Mueller-Stahl
Benedict Arnold	Hans-Georg Hess, Isabelle Eberhardt, Günther Heydemann, Max Schreck, Louis Blenker
Bill Gates	Ferdinand von Zeppelin, Günther Jauch, Nikolaus Harnoncourt, Sepp Blatter, Alfred Grosser
Britney Spears	Herta Müller, Günter Grass, Joachim Gauck, Hans-Dietrich Genscher, Koča Popović
Donald Trump	Max Frisch, Thomas Gottschalk, Jan Josef Liefers, Rainer Werner Fassbinder, Christa Wolf
Elvis Presley	Reinhard Lakomy, James Last, Herbert Achternbusch, Fritz Hauser, Hans-Peter Pfammatter
Ernest Hemingway	Karlheinz Böhm, Ricarda Huch, Michael Ballhaus, Arnold Zweig, Michael Fassbender
Frank Lloyd Wright	Ferdinand Hodler, Johan Zoffany, Hans Thoma, Arne Jacobsen, Lucas Cranach the Younger
George Washington	Friedrich Wilhelm von Seydlitz, Dagobert Sigmund von Wurmser, Heinz Guderian, Ernst Gideon von Laudon, George Olivier, count of Wallis
Henry Ford	Heinz Sielmann, Wieland Schmied, Manfred Krug, Paul Maar, Armin Mueller-Stahl
Hillary Clinton	Pope Benedict XVI, Willy Brandt, Angela Merkel, Helmut Schmidt, Kurt Biedenkopf
Homer Simpson	Elizabeth Lavenza, Hans Fugger, Baron Strucker, Herbert of Wetterau, Prince Johannes of Liechtenstein
Jimi Hendrix	Marius Müller-Westernhagen, Karl Richter, Reinhard Lakomy, Michael Cretu, Paul van Dyk
Kim Kardashian	Erika Mann, Frank Wedekind, Til Schweiger, Fritz von Opel, Carmen Electra
Marilyn Monroe	Gerhart M. Riegner, Viktor de Kowa, Otto Sander, Hans Hass, Dorothee Sölle
Michael Jordan	Jean-Claude Juncker, Richard von Weizsäcker, Herta Müller, Konrad Adenauer, Helmut Kohl
Louis Armstrong	Herbert Prikopa, Till Lindemann, Nico, Klaus Voormann, Jakob Adlung
Neil Armstrong	Stefan Hell, Franz-Ulrich Hartl, Reinhard Genzel, Charles Weissmann, Harald zur Hausen
Noam Chomsky	Günter Grass, Herta Müller, Heinrich Böll, Peter Handke, Juli Zeh
Oprah Winfrey	Günter Grass, Peter Scholl-Latour, Elfriede Jelinek, Juli Zeh, Christa Wolf
Orville Wright	Frank Thiess, Jessica Hausner, Elmar Wepper, Wolf Jobst Siedler, Marc Rothemund
Richard Nixon	Heinrich von Brentano, Ernst Benda, Gustav Heinemann, Heiner Geißler, Heinrich Albertz
Superman	Magneto, Nightcrawler, Sinterklaas, Silent Night, Victor Frankenstein

Steve Jobs	Victor Klemperer, Joschka Fischer, Jürgen Kuczynski, Joachim Fest, Dieter Hallervorden
Steven Spielberg	Herta Müller, Jean-Claude Juncker, Hans-Dietrich Genscher, Joachim Gauck, Koča Popović
Tiger Woods	Charles Dutoit, Shania Twain, Lise Meitner, Michael Haneke, Otto Hahn
Walt Disney	Shania Twain, Charles Dutoit, Lise Meitner, Otto Hahn, Michael Haneke
John F. Kennedy	Bernhard von Bülow, Otto von Habsburg, Hans-Jochen Vogel, Prince Henry of Prussia, Frederick Augustus III of Saxony
Charles Lindbergh	Pina Bausch, Ferdinand von Zeppelin, Nikolaus Harnoncourt, Jan Josef Liefers, Wolf Biermann
Rosa Parks	Hermann Lenz, Wilhelm Feldberg, Horst Tappert, Peter Stein, Gert Jonke
Serena Williams	Charles Dutoit, Lise Meitner, Michael Haneke, Richard von Coudenhove-Kalergi, Klaus Clusius

Table 7: We show top-5 predictions out of the top-100 for American→German adaptations on the Veale NOC subset using **WikiData**. These are compared to our human annotations in our results.

Entity	Top Five 3CosAdd Adaptations: American→German adaptations on the Veale NOC
Abraham Lincoln	Napoleon, Napoléon Bonaparte, Erzherzog Johann, Otto von Bismarck, Kaiser Wilhelm II.
Al Capone	Nazis, SA-Mann, Verhaftungswellen, Judenverfolgung, Fluchthilfe
Alfred Hitchcock	Fritz Lang, Helmut Käutner, Willi Forst, Emil Jannings, Heinz Rühmann
Benedict Arnold	Russlandfeldzug 1812, Schlacht bei Roßbach, Jean-Victor Moreau, schwedischen Armee, Alexander Wassiljewitsch Suworow
Bill Gates	congstar, Alnatura, GMX, ChessBase, Gardeur
Britney Spears	Glasperlenspiel, Unheilig, Helene Fischer, Christina Aguilera, Herbert Grönemeyer
Charles Lindbergh	Segelflieger, Flugpioniere, Zeppelins, Adolf Hitler, Caproni
Donald Trump	Deutschland, Österreich, Trump, Strache, Bundestagswahlkampf
Elvis Presley	Udo Jürgens, Elvis Presley, Hits, den Beatles, der Beatles
Ernest Hemingway	Stefan Zweig, Franz Werfel, Joachim Ringelnatz, Hermann Hesse, Gottfried Benn
Frank Lloyd Wright	Adolf Loos, Le Corbusier, Bruno Schmitz, Entwürfen, Fritz Höger
George Washington	Napoléon Bonaparte, Friedrich dem Großen, Napoleon, Friedrich der Große, Napoleon Bonaparte
Henry Ford	Ferdinand Porsche, Büssing, Krupp, Ettore Bugatti, Steyr-Daimler-Puch
Hillary Clinton	Deutschland, Bundestagswahlkampf, Österreich, Sarkozy, Strache
Homer Simpson	Eingangsszene, verulkt, Schlusssequenz, Off-Stimme, Muminfamilie
Jack The Ripper:Ripper	Tat, Werwolf, Täter, Dritten Reich, Mörder
Jay Z	Xavier Naidoo, D-Bo, Sido, Rosenstolz, David Guetta
Jimi Hendrix	Udo Jürgens, Tangerine Dream, Jimi Hendrix, Pink Floyd, Depeche Mode
John F. Kennedy	Adolf Hitler, Bundeskanzlers, Adolf Hitlers, Adolf Hitler, Hitler
Kim Kardashian	Kaas, gotv, Frank Zander, Herbert Grönemeyer, Roland Kaiser
Louis Armstrong	Richard Tauber, Django Reinhardt, Udo Jürgens, Sidney Bechet, Jazzorchester
Marilyn Monroe	Marlene Dietrich, Lil Dagover, Elisabeth Bergner, Brigitte Bardot, Romy Schneider
Michael Jordan	Powerplay, Xavi, Predrag Mijatović, NHL-Historie, Franck Ribéry
Neil Armstrong	Juri Gagarin, Vorbeiflug, Weltraum, Raumstation Mir, Raumfahrer
Noam Chomsky	Jürgen Habermas, Hans-Ulrich Wehler, Carl Schmitt, Theodor W. Adorno, Norbert Elias
Oprah Winfrey	Harald Schmidt, Thomas Gottschalk, Satiresendung, ORF-Sendung, Hape Kerkeling
Orville Wright	Parseval, Luft Hansa, Hugo Junkers, Ernst Heinkel, Claude Dornier
Richard Nixon	Österreich, Deutschland, Bundeskanzler, Bundeskanzlers, Bundespräsidenten
Rosa Parks	NS-Militärjustiz, Franz Jägerstätter, NS-Opfer, Bücherverbrennung, Baum-Gruppe
Serena Williams	Dick Jaspers, Philipp Kohlschreiber, Semifinale, Achtelfinale, Dominic Thiem
Steve Jobs	Steve Jobs, Sony, Electronic Arts, Netscape, Atari

Steven Spielberg	Hörspielproduktion, Helmut Käutner, Fellini, Oliver Hirschbiegel, Kinofilm
Superman	Superman, Batman, Superhelden, Monster, Spider-Man
Tiger Woods	Rekordeuropameister, Österreich, spanische Team, ÖFB-Cupsieger, Deutschland
Walt Disney	Fritz Lang, Sascha-Film, Fellini, UFA, "Das Cabinet des Dr. Caligari"

Table 8: We show top-5 predictions out of the top-100 for American→German adaptations on the Veale NOC subset using **3CosAdd**. These are compared to our human annotations in our results.

Entity	Top Five Learned Adaptations: American→German adaptations on the Veale NOC
Abraham Lincoln	Konrad Adenauer, Helmut Schmidt, Willy Brandt, Helmut Kohl, Adenauer
Al Capone	Andreas Baader, Leo Katzenberger, Paul Schäfer, Strippel, Hermann Langbein
Alfred Hitchcock	Helmut Käutner, Til Schweiger, Mario Adorf, Paul Verhoeven, Dennis Hopper
Benedict Arnold	Otto von Bismarck, Bismarcks, Bismarck, Preußens, Kaiserreiches
Bill Gates	Martin Winterkorn, Volkswagen AG, DaimlerChrysler, Robert Bosch GmbH, Volkswagen AG
Britney Spears	Sarah Connor, Nena, Helene Fischer, Lena Meyer-Landrut, Moses Pelham
Charles Lindbergh	Chaim Weizmann, Tomáš Garrigue Masaryk, Ferdinand Sauerbruch, Fritz Haber, Chaim Arlosoroff
Donald Trump	Helmut Schmidt, Angela Merkel, Gerhard Schröder, Helmut Kohl, Bundesaußenminister
Elvis Presley	Udo Jürgens, Peter Maffay, Cliff Richard, Achim Reichel, Lou Reed
Ernest Hemingway	Paul Schlenther, Marcel Reich-Ranicki., Timothy Leary, Erwin Leiser, Alice Walker
Frank Lloyd Wright	Albert Einstein, Max Planck, Max Born, Hermann von Helmholtz, Arnold Sommerfeld
George Washington	Otto von Bismarck, Otto von Bismarck, Konrad Adenauer, Engelbert Dollfuß, Joseph Wirth
Henry Ford	Ernst Abbe, Carl Duisberg, Bubbe, Aby Warburg, Sybel
Hillary Clinton	Angela Merkel, Angela Merkel, Helmut Schmidt, Gerhard Schröder, Bundesinnenminister
Homer Simpson	Rolf Hochhuth, Carl Bernstein, Uwe Tellkamp, Wolfgang Völz, Richard Gere
Jack The Ripper:Ripper	Sarah Connor, Spike Jonze, Timberlake, "Das Urteil", "Nichts als die Wahrheit"
Jay Z	will.i.am, Moses Pelham, Silbermond, Xavier Naidoo, Kanye West
Jimi Hendrix	Peter Maffay, Udo Lindenberg, Depeche Mode, Xavier Naidoo, Die Toten Hosen
John F. Kennedy	Konrad Adenauer, Helmut Schmidt, Willy Brandt, Helmut Kohl, Bundeskanzler
Kim Kardashian	Heidi Klum, Ruth Moschner, Ellen DeGeneres, Circus HalliGalli, Oliver Pocher
Louis Armstrong	Peter Maffay, Radioaufnahmen, Udo Lindenberg, Achim Reichel, Helge Schneider
Marilyn Monroe	Walter Giller, Jessica Tandy, Liv Ullmann, Edgar Selge, Betty White
Michael Jordan	Dirk Nowitzki, Toni Kroos, Zlatan Ibrahimović, Xavi, Zinédine Zidane
Neil Armstrong	Max von Laue, Albert Einstein, Chaim Weizmann, Johannes R. Becher, Ernst Abbe
Noam Chomsky	Albert Einstein, Nobelpreisträger, Max Planck, American Psychological Association, Hans Bethe
Oprah Winfrey	Anja Kling, "Forsthaus Falkenau", Uschi Glas, "Saturday Night Live"., Anke Engelke

Orville Wright	Kawaishi, Rjabuschinski, Monistenbund, Dethmann, Leo Baeck Instituts
Richard Nixon	Helmut Schmidt, Konrad Adenauer, Willy Brandt, Helmut Kohl, Gerhard Schröder
Rosa Parks	Sophie Scholl, Die letzten Tage, Emil Jannings., Ruth Wilson, Monica Bleibtreu
Serena Williams	Max Schmeling, Wilfried Dietrich, Gottfried von Cramm, Henry Maske, László Kubala
Steve Jobs	DaimlerChrysler, Volkswagen, Siemens, Sanyo, Fujitsu
Steven Spielberg	Til Schweiger, Ethan Hawke, Matthias Schweighöfer, Samuel L. Jackson, Ryan Reynolds
Superman	Jabberwocky, Freaks, Scarface, Leatherface, Krabat
Tiger Woods	Dirk Nowitzki, deutschen U21-Nationalmannschaft, MTV Gießen, Mats Hummels, Franz Beckenbauer
Walt Disney	Helmut Dietl, Peter Ustinov, David Mamet, Rainer Werner Fassbinder, Sönke Wortmann

Table 9: We show top-5 predictions out of the top-100 for American→German adaptations on the Veale NOC subset with our **Learned Adaptation** approach. These are compared to our human annotations in our results.