

# Data Visualization for Machine Learning

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Google Brain

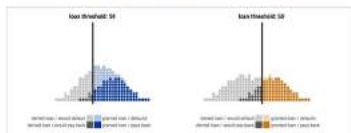
### Embedding Projector

an open source, visualization tool for high-dimensional data



### Fairness in ML

Try different tradeoffs yourself to understand issues around fairness and machine learning.



### Machine Translation

Visualizing how a translation network learns an "interlingua" or universal language.



### Geodetic Velocities Visualization

an open source visualization of earthquake-cycle physics



### TensorFlow Playground

an open source, transparent neural net you can play with in your browser



### Unfiltered News

see news coverage around the world and spot underreported stories (a collaboration with Jigsaw)



### TensorFlow Graph Visualizer

an open source, high-level view of tensorflow computation graphs



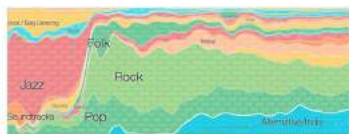
### Periodic Table

a twist on the classic visualization of the atomic elements



### Music Timeline

see how different musical genres become popular over time, and discover artists in each genre



### Digital Attack Map

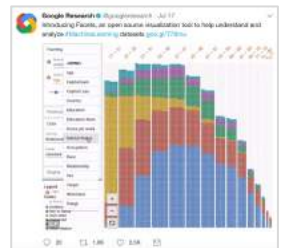
see live data on denial-of-service attacks across the world, and observe historical patterns



# PAIR | People + AI Research Initiative

Bringing Design Thinking and HCI to Machine Learning  
[google.ai/pair](http://google.ai/pair)

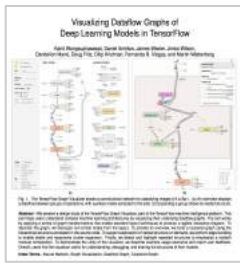
Open Source tools  
and platforms



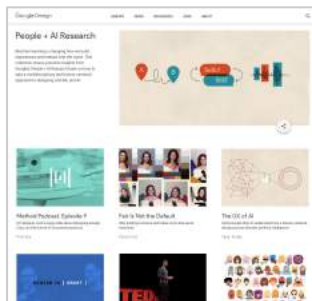
Educational  
Materials



Academic  
Publications



Public presentations,  
sharing best practices



Public Symposia  
& meetings



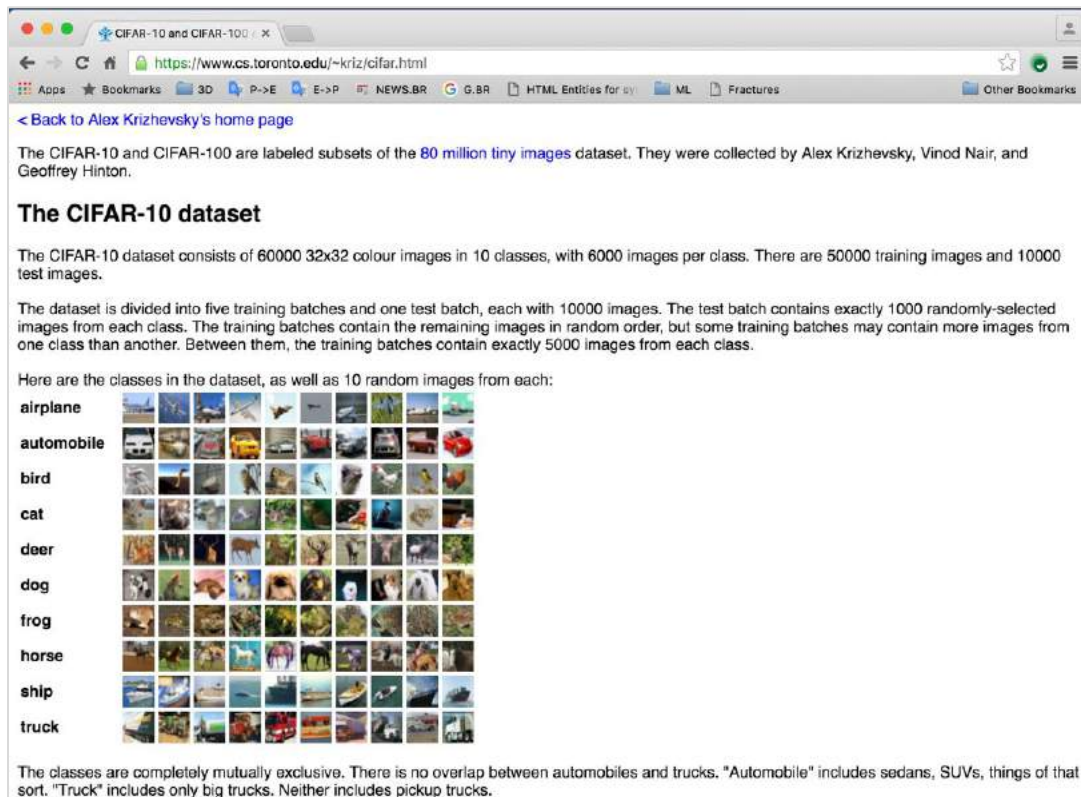
Visiting Faculty,  
Faculty Grants



Training data  
is crucial

Debug your data before  
debugging your model

# Let's start with a data set you might have heard of



The screenshot shows a web browser window with the address bar containing <https://www.cs.toronto.edu/~kriz/cifar.html>. The page content includes a link to Alex Krizhevsky's home page, a paragraph describing the CIFAR-10 and CIFAR-100 datasets as subsets of an 80 million tiny images dataset, and a section titled "The CIFAR-10 dataset". This section explains that the dataset consists of 60,000 32x32 color images in 10 classes, with 50,000 training images and 10,000 test images. It also details the division into five training batches and one test batch. Below the text, there is a list of 10 classes with corresponding 10x10 grids of random images from each class: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. A final paragraph clarifies that the classes are mutually exclusive and provides specific inclusions for "Automobile" and "Truck".

< Back to Alex Krizhevsky's home page

The CIFAR-10 and CIFAR-100 are labeled subsets of the **80 million tiny images** dataset. They were collected by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton.

## The CIFAR-10 dataset

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class.

Here are the classes in the dataset, as well as 10 random images from each:

- airplane
- automobile
- bird
- cat
- deer
- dog
- frog
- horse
- ship
- truck

The classes are completely mutually exclusive. There is no overlap between automobiles and trucks. "Automobile" includes sedans, SUVs, things of that sort. "Truck" includes only big trucks. Neither includes pickup trucks.

32 x 32 images  
10 classes

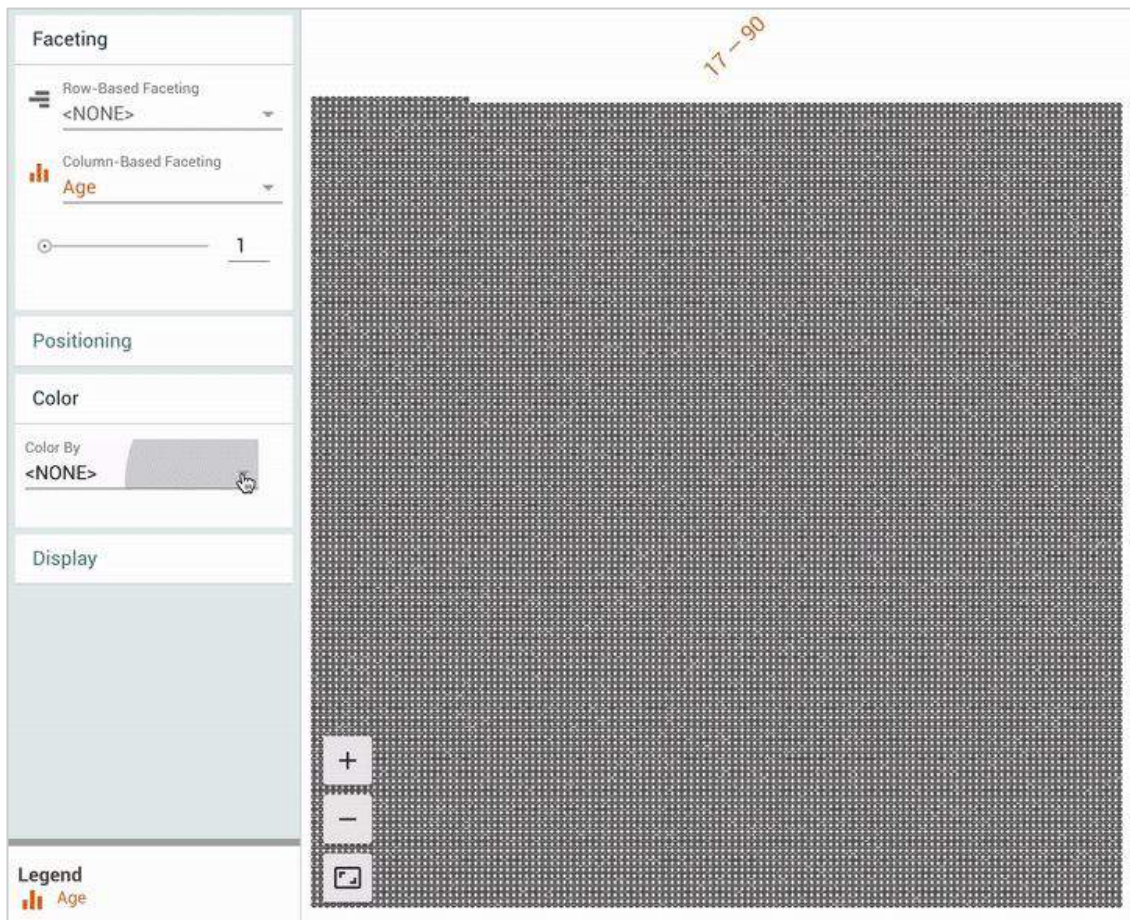




# Facets

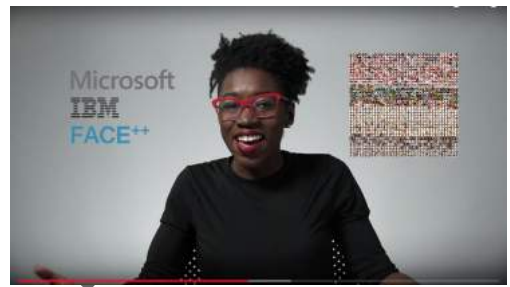
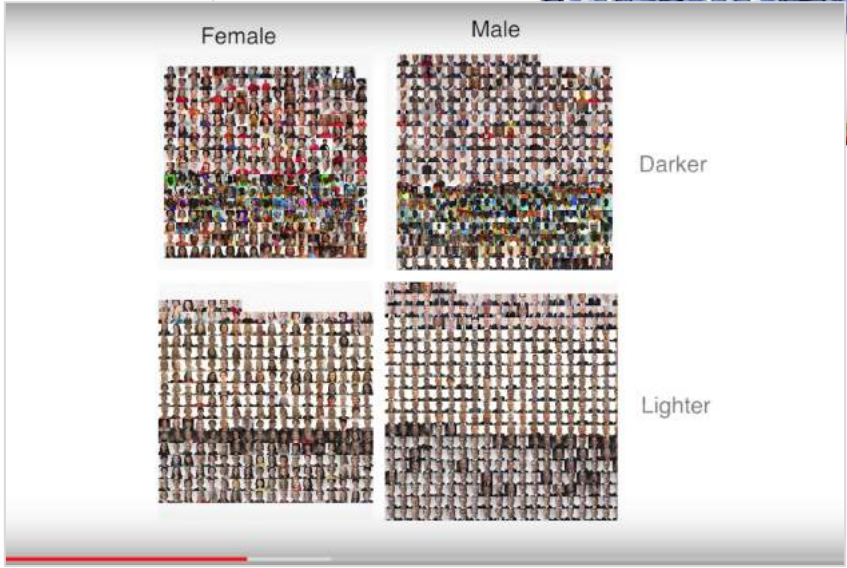
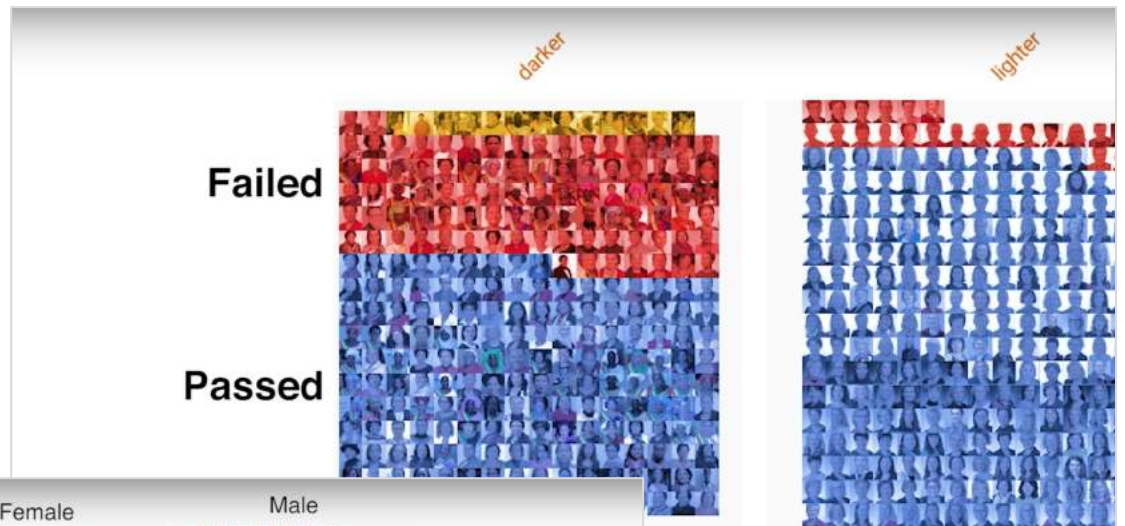
Open-source

[pair-code.github.io/facets](https://pair-code.github.io/facets)



# Gender Shades

Joy Buolamwini  
MIT Media Lab



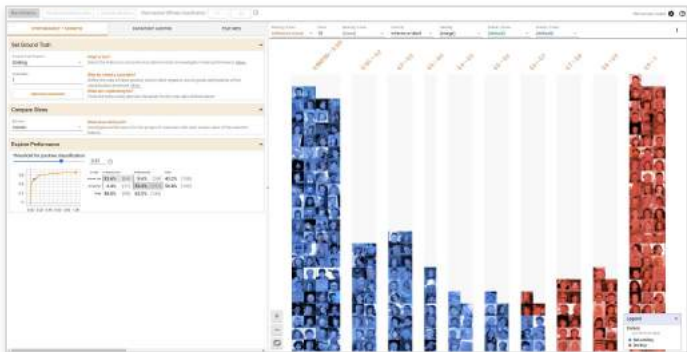


# What-If Tool

open source

code-free ML probing

[pair-code.github.io/what-if-tool](https://pair-code.github.io/what-if-tool)



What-if Tool demo - binary classifier for predicting salary of over \$50k - UCI census income dataset

Partial dependence plots    Compute distance    Show nearest different classification: L1    L2   

PERFORMANCE + FAIRNESS    **DATAPoint EDITOR**    FEATURES

Binning | X Axis: age    Co. | Binning | Y Axis: marital-stat    C. | Color By: Inference

**Select a datapoint to begin exploring features and values.** →

Clicking on a datapoint in the visualization will load all the features and values associated with that example. Here are some of the things you can do:

- **Edit features and values and rerun inference** to see how your model performs.
- **Compute Distance**: Select an example to be an anchor and create a new L1 or L2 distance feature for all loaded examples.
- **Closest Counterfactuals**: For classification models, find the closest example with a different classification using L1 or L2 distance.
- **Partial Dependence Plots**: For a selected example, explore plots for every feature that show the change in inference results across different valid values for that feature.

**Use the Performance + Fairness tab to investigate model performance across your dataset.**

**Use the Features tab to view statistics about your dataset.**

# What-If Tool

## Fairness metrics

### Compare Slices

Slice by **Mouth\_Slightly\_Open** [What does slicing do?](#)  
Investigate performance for the groups of examples with each unique value of the selected feature.

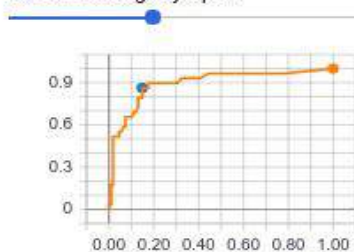
Slice by (secondary) **<none>**  
Specify a second feature to slice the data by.

Optimize sliced thresholds for: [What are I optimizing for? More](#)

**Individual thresholds** Equal opportunity Equal accuracy Demographic parity Single threshold

### Explore Performance

#### Mouth not slightly open



0.41



	Predicted Yes	Predicted No	Total
Actual Yes	18.2% (25)	2.9% (4)	21.2% (29)
Actual No	11.7% (16)	67.2% (92)	78.8% (108)
Total	29.9% (41)	70.1% (96)	

#### Mouth slightly open

0.82



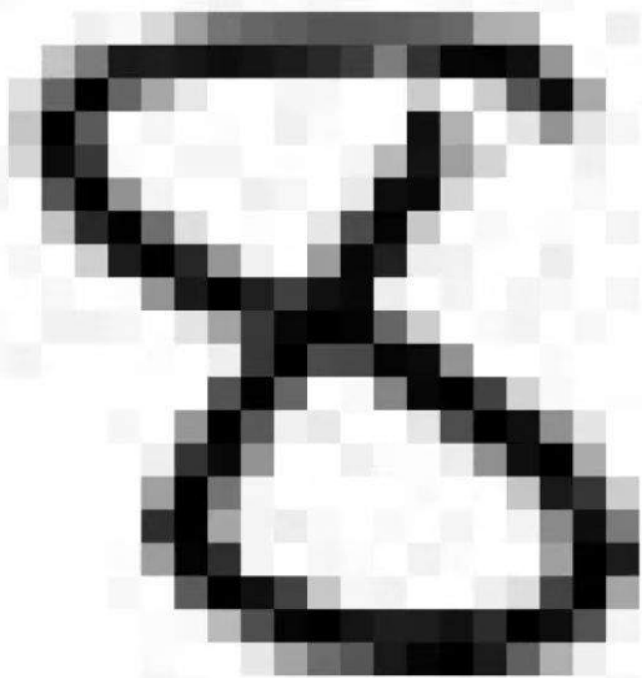
# Model Understanding

Looking into high-dimensional  
spaces

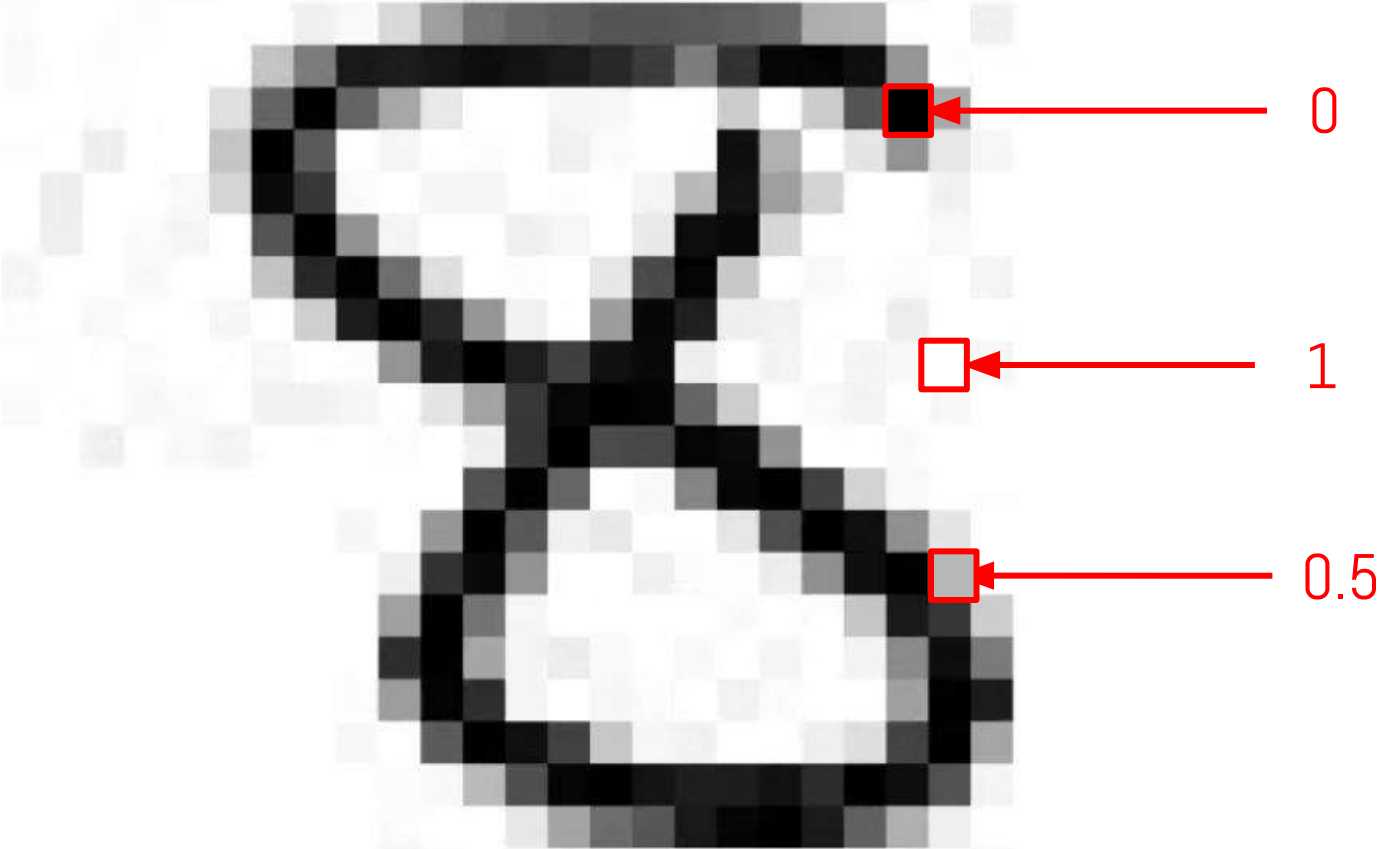




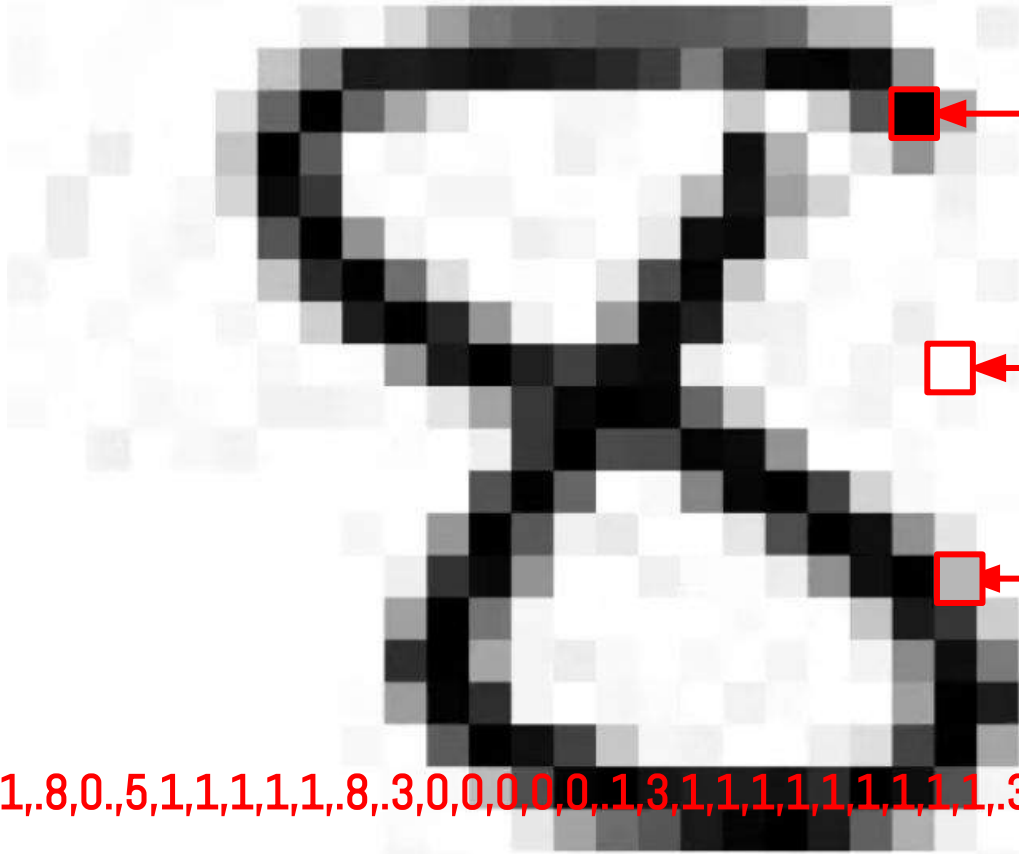
## Images as vectors



# Images as vectors



# Images as vectors



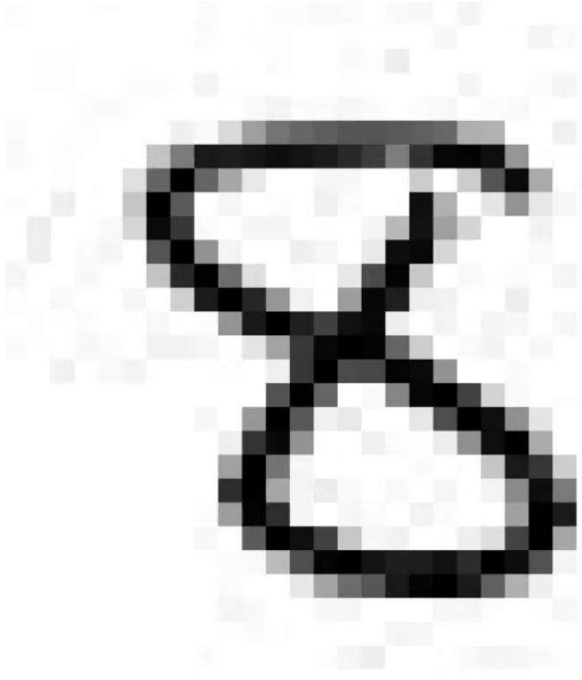
0

1

0.5

(1,1,1,1,1,1,1,1,1,8,0,5,1,1,1,1,1,8,3,0,0,0,0,0,1,3,1,1,1,1,1,1,1,1,3,1,0,0,0,0,0,0,4,9,1, ... )

We've turned this image



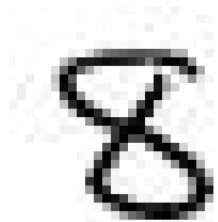
into this vector

(1,1,1,1,1,1,1,1,1,8,0,5,1,1,1,...)

784 pixels → 784 dimensions



We've turned this image



into this vector

(1,1,1,1,1,1,1,1,1,**1**,**.8**,**0**,**.5**,**1**,1,1,...)

784 pixels → 784 dimensions



(1,1,1,1,1,1,1,1,1,**.6**,**.7**,**0**,**.4**,**1**,1,1,...)



(1,1,1,1,1,1,1,1,1,**.4**,**.5**,**0**,**.3**,**.2**,1,1,...)

⋮

# Embedding projector

## MNIST visualization

# Model interpretability use case

Multi-lingual translation

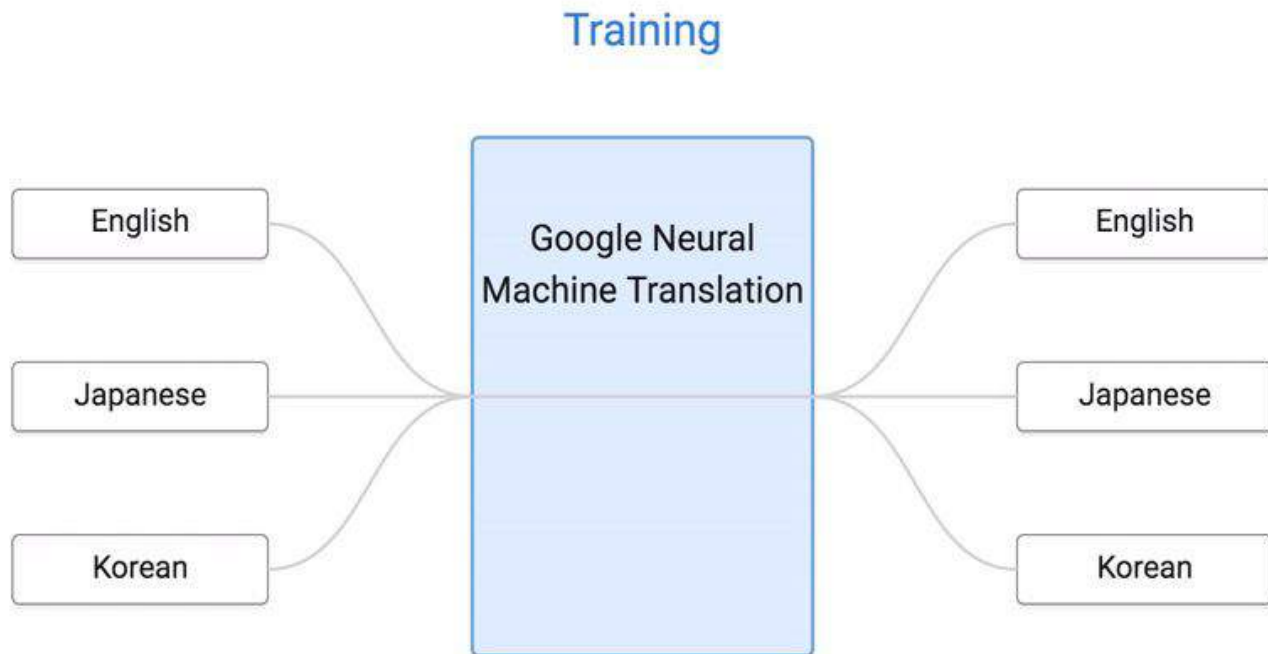
What does the language embedding space look like?

<https://arxiv.org/abs/1611.04558>

Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation

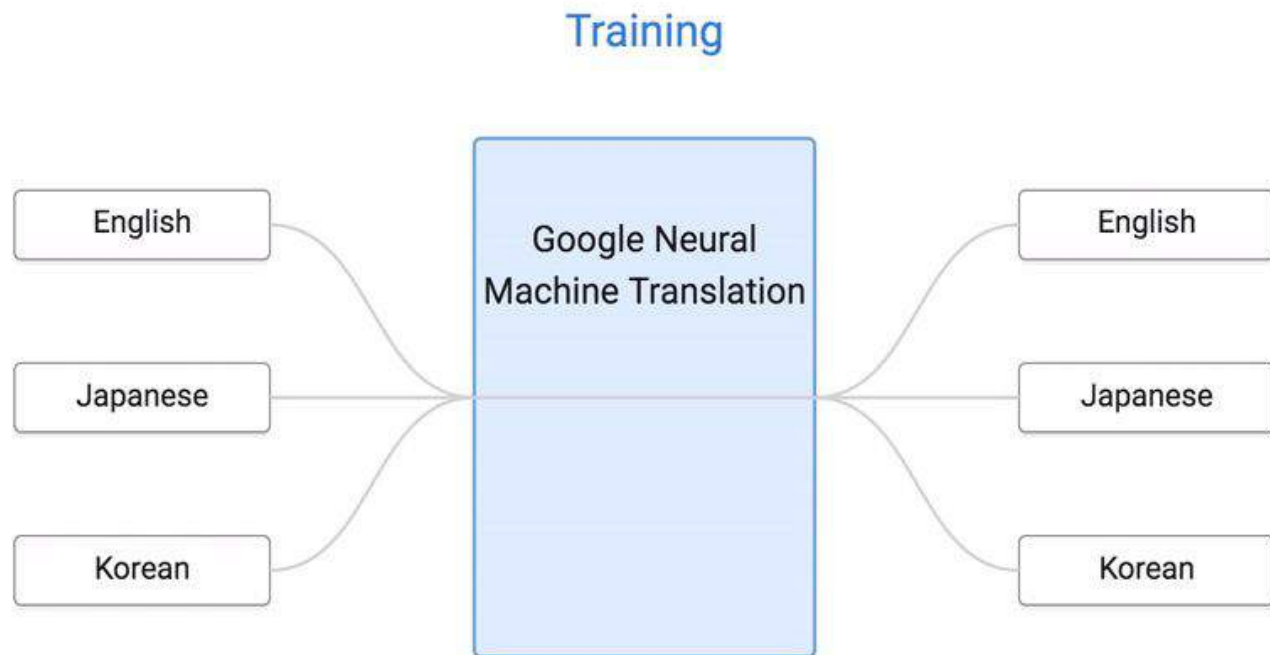
Melvin Johnson, Mike Schuster, Quoc V. Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, Macduff Hughes, Jeffrey Dean

**Training:** English ← → Japanese  
English ← → Korean

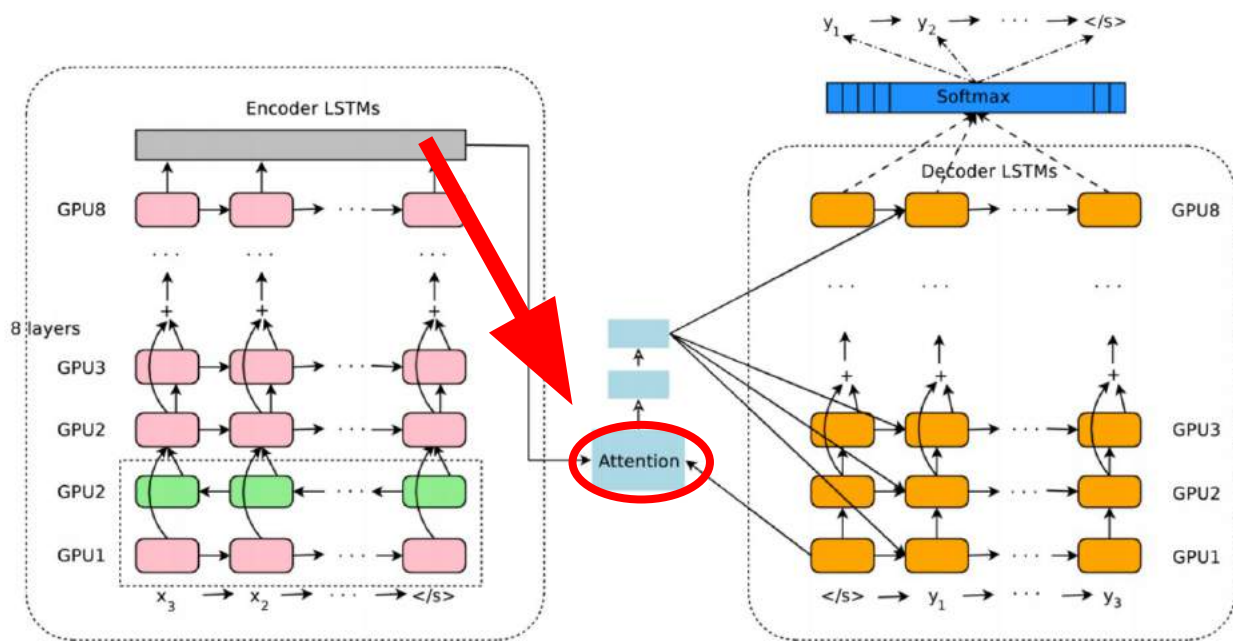




**Training:** English  $\leftarrow \rightarrow$  Japanese  
English  $\leftarrow \rightarrow$  Korean  
Japanese  $\leftarrow \rightarrow$  Korean (zero shot)

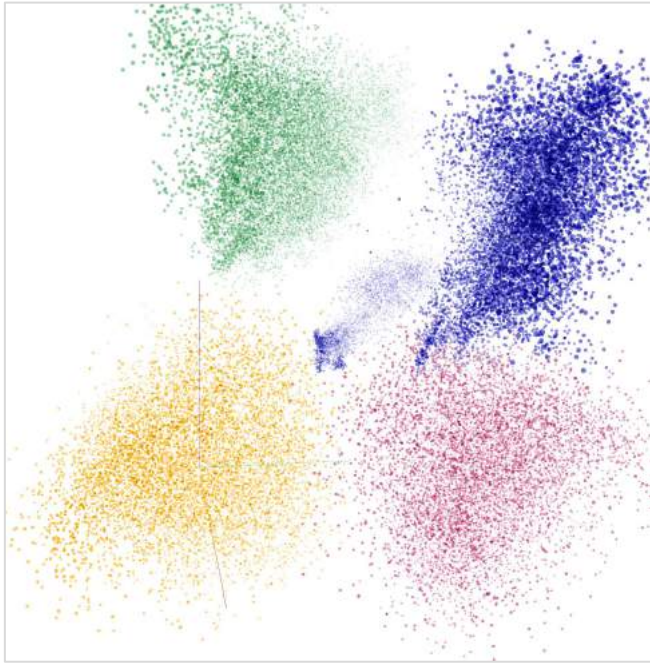


# Visualize internal representation ("embedding space")

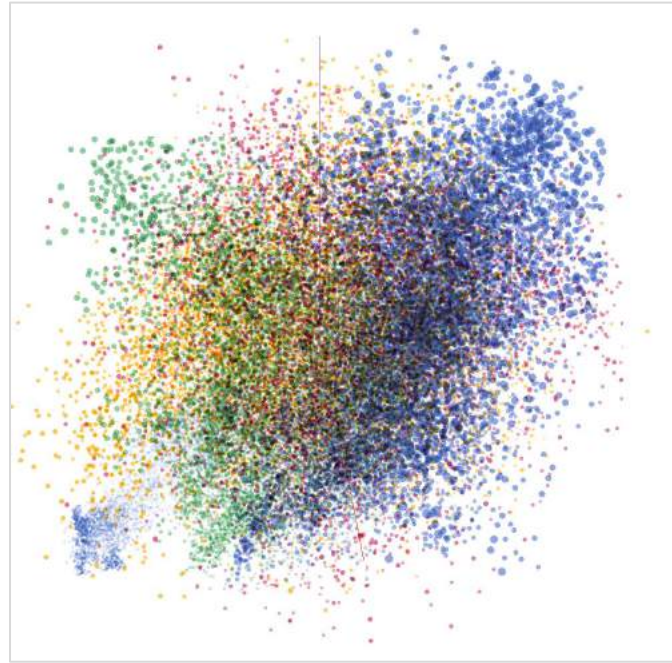


# Research question

What does the multi language embedding space look like?



or



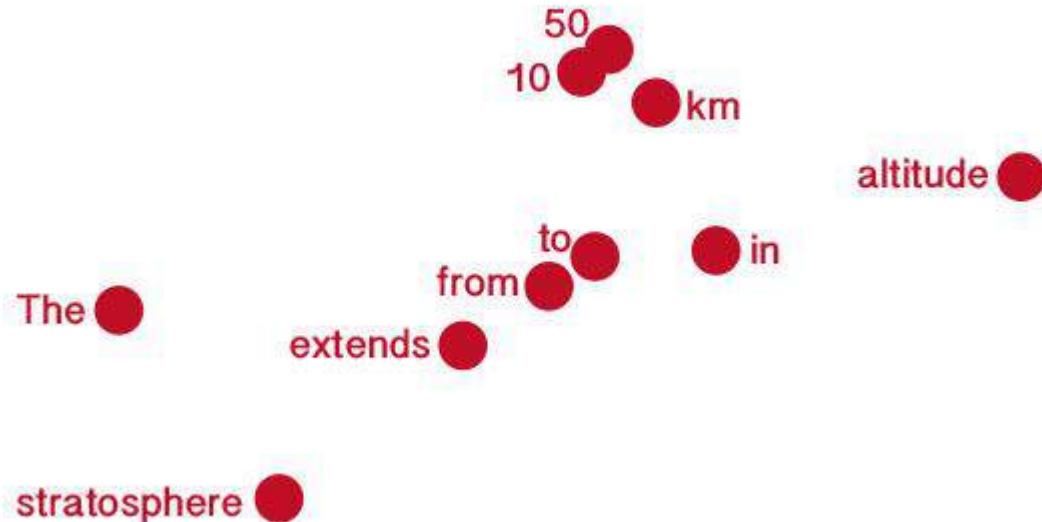
Note: not real data

What does a sentence look like in embedding space?  
(points in 1024-dim space: the data that the decoder receives)

E.g. “*The stratosphere extends from 10km to 50km in altitude*”

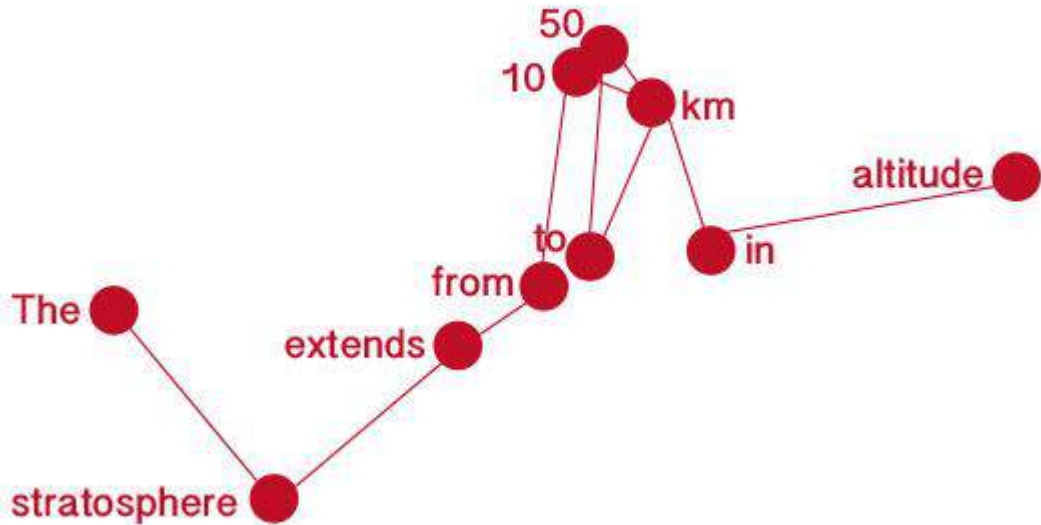


# What does a sentence look like in embedding space?



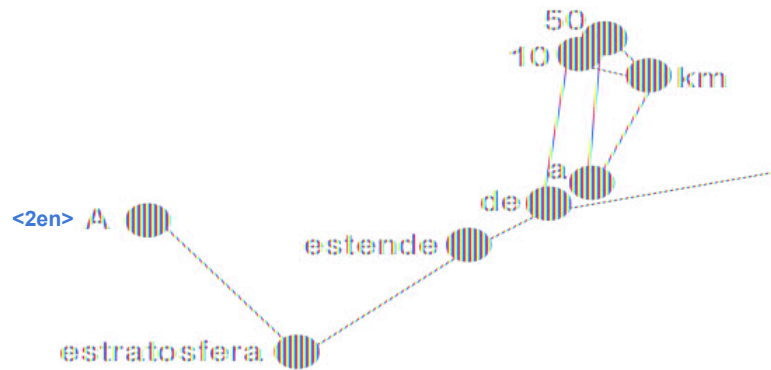
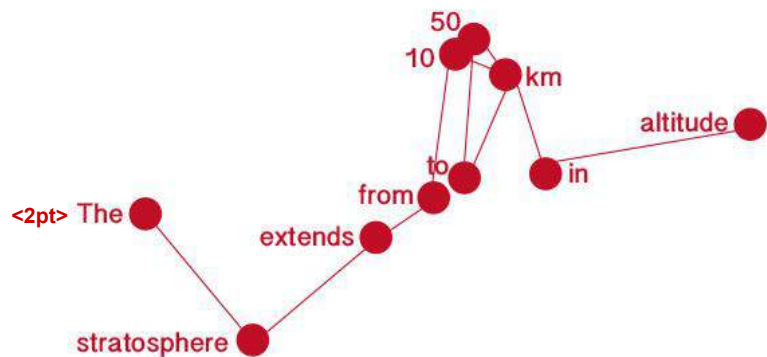
Note: simplification of real situation!

# What does a sentence look like in embedding space?



What do **parallel** sentences look like in embedding space?  
(same meaning, different language)

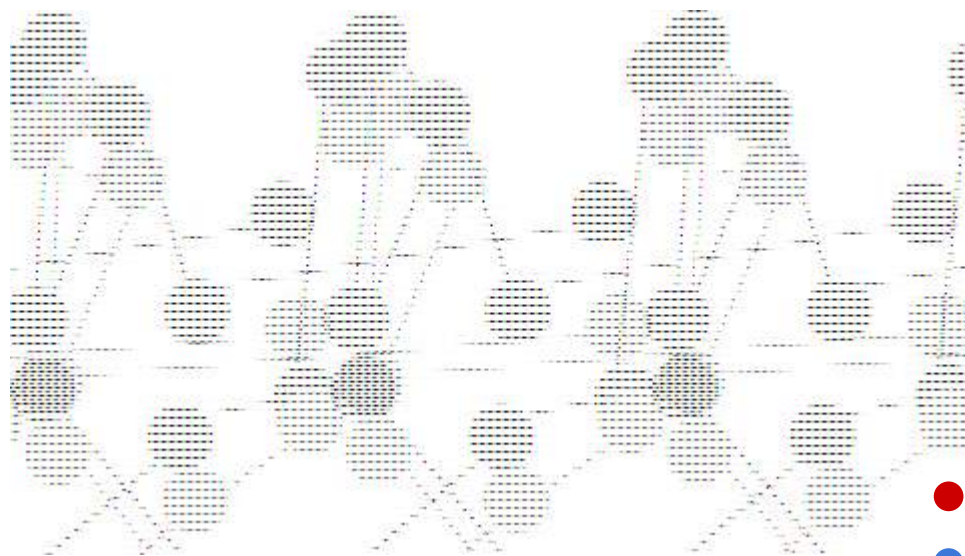
like this?



- English
- Portuguese

What do **parallel** sentences look like in embedding space?  
(same meaning, different language)

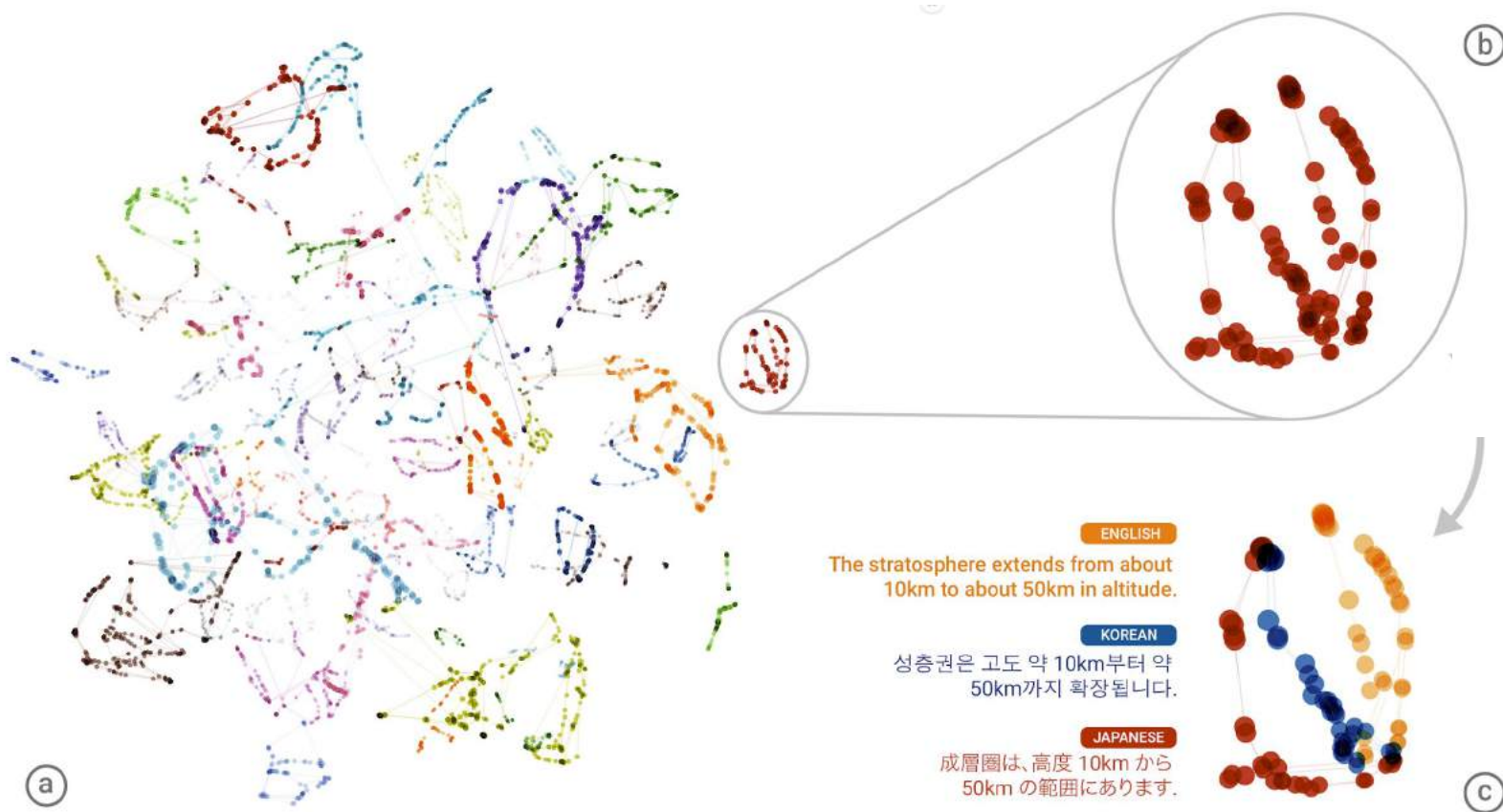
or like this?



- English
- Portuguese

# Interlingua?

Sentences with the same meaning mapped to similar regions regardless of language!



Distance between bridge / non-bridge sentences is inversely related to translation quality

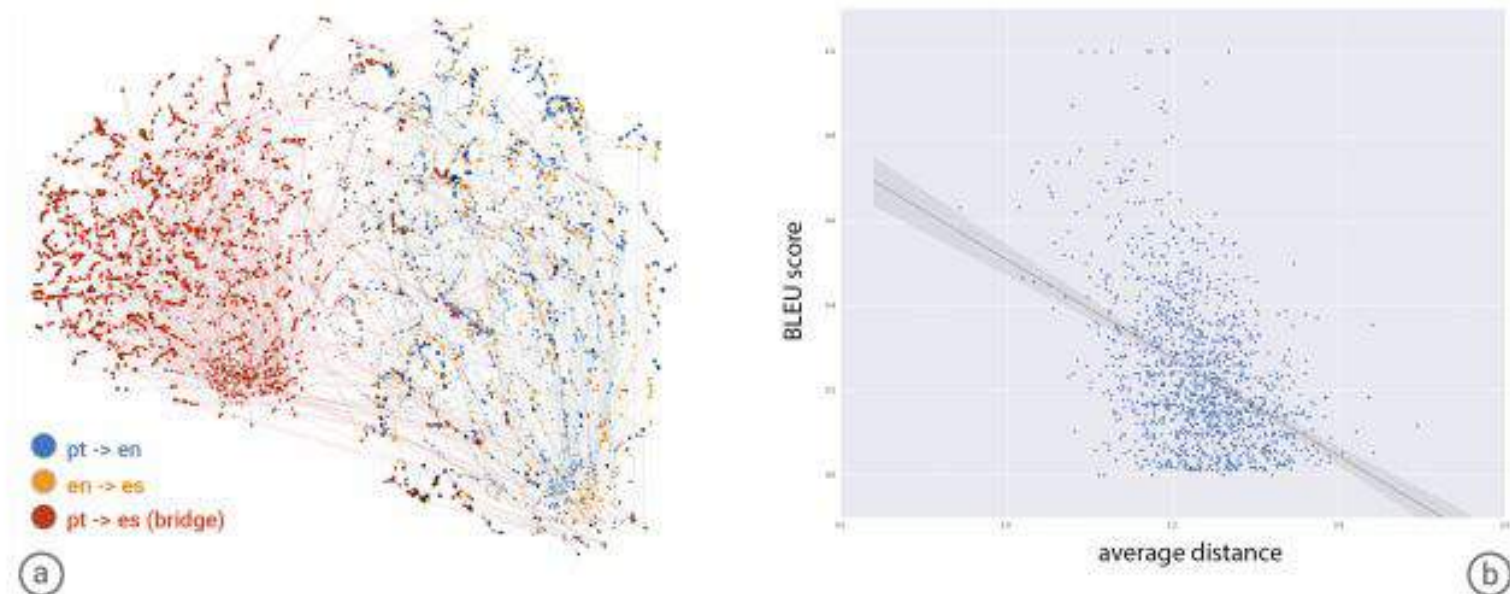
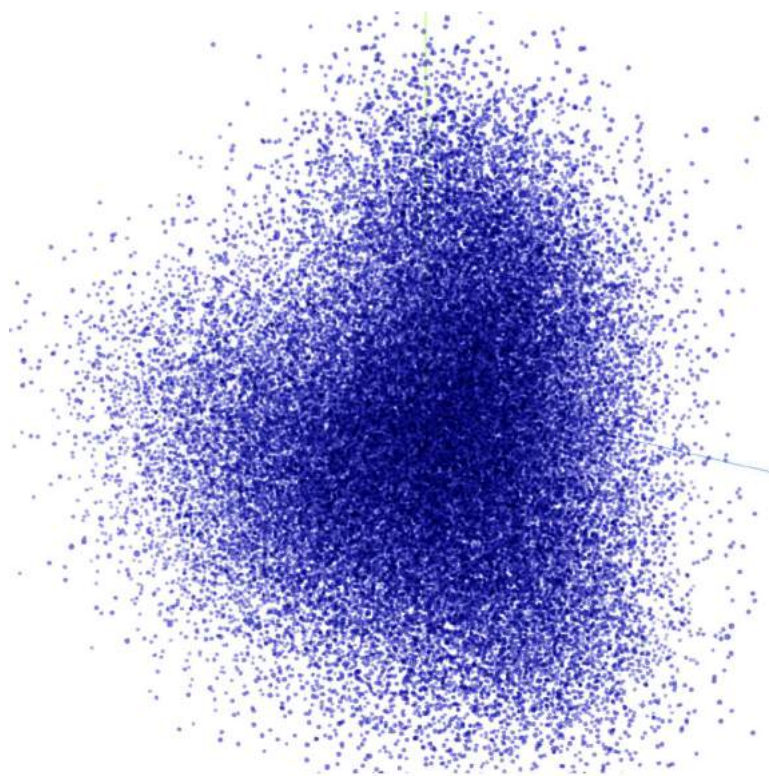


Figure 3: (a) A bird's-eye view of a t-SNE projection of an embedding of the model trained on Portuguese→English (blue) and English→Spanish (yellow) examples with a Portuguese→Spanish zero-shot bridge (red). The large red region on the left primarily contains the zero-shot Portuguese→Spanish translations. (b) A scatter plot of BLEU scores of zero-shot translations versus the average point-wise distance between the zero-shot translation and a non-bridged translation. The Pearson correlation coefficient is  $-0.42$ .



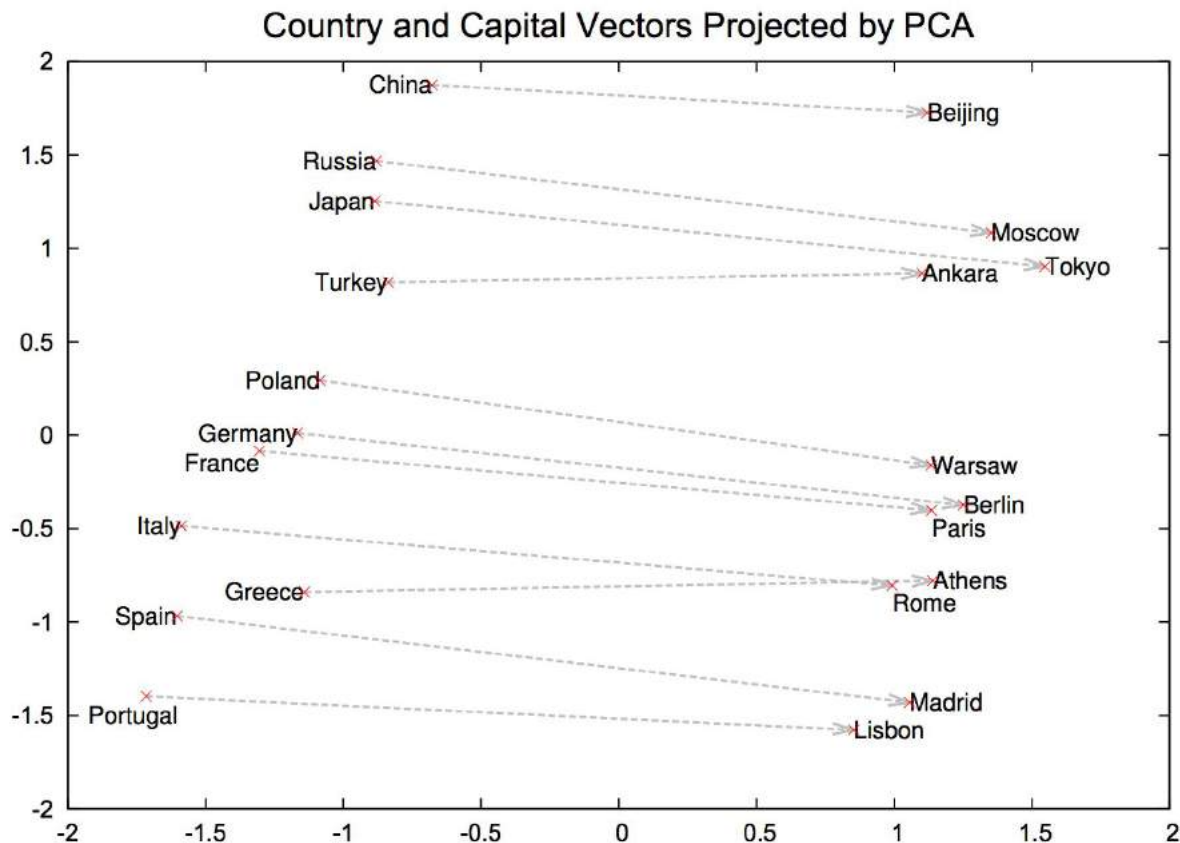


word embeddings

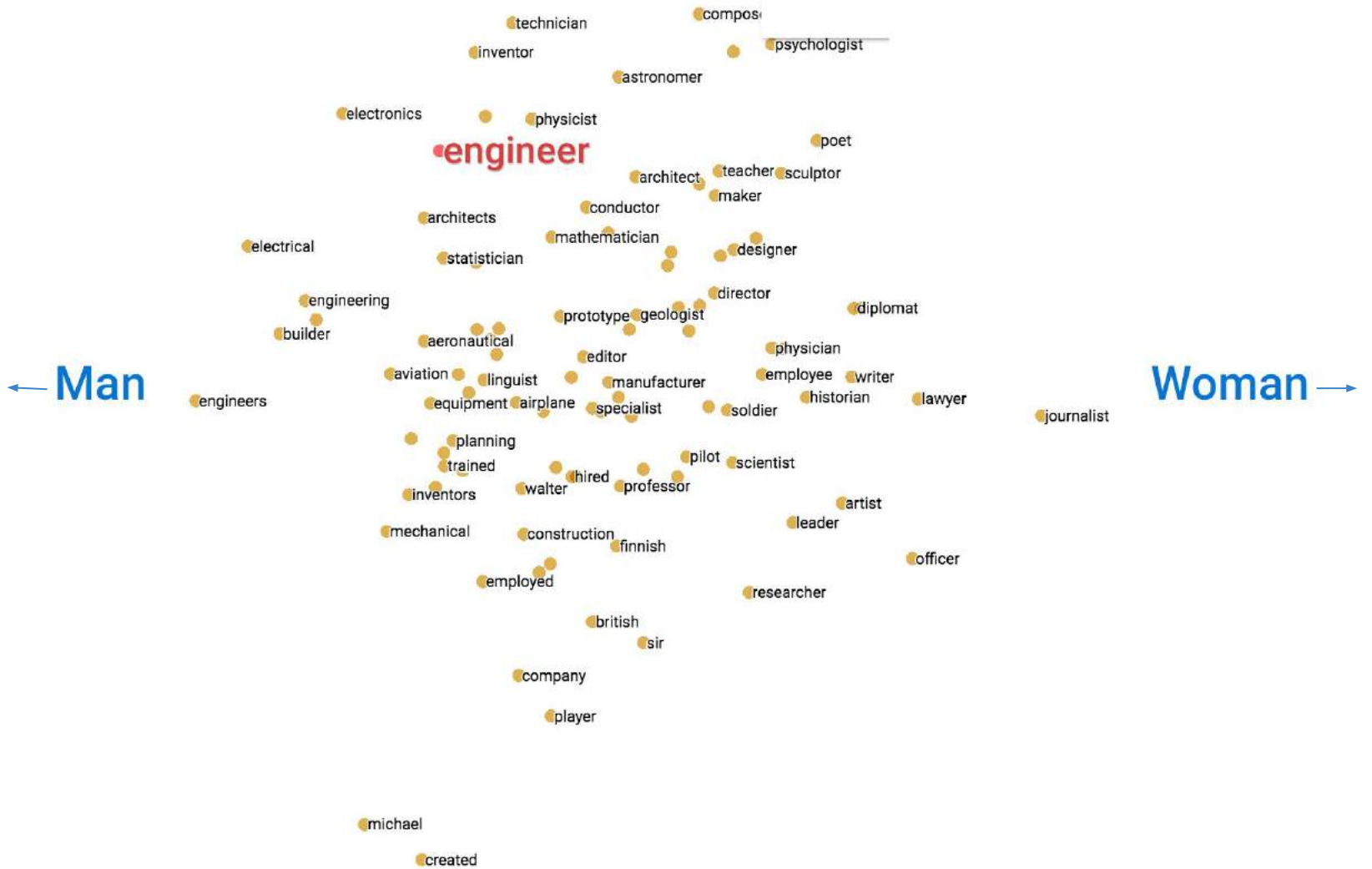


# Word embeddings

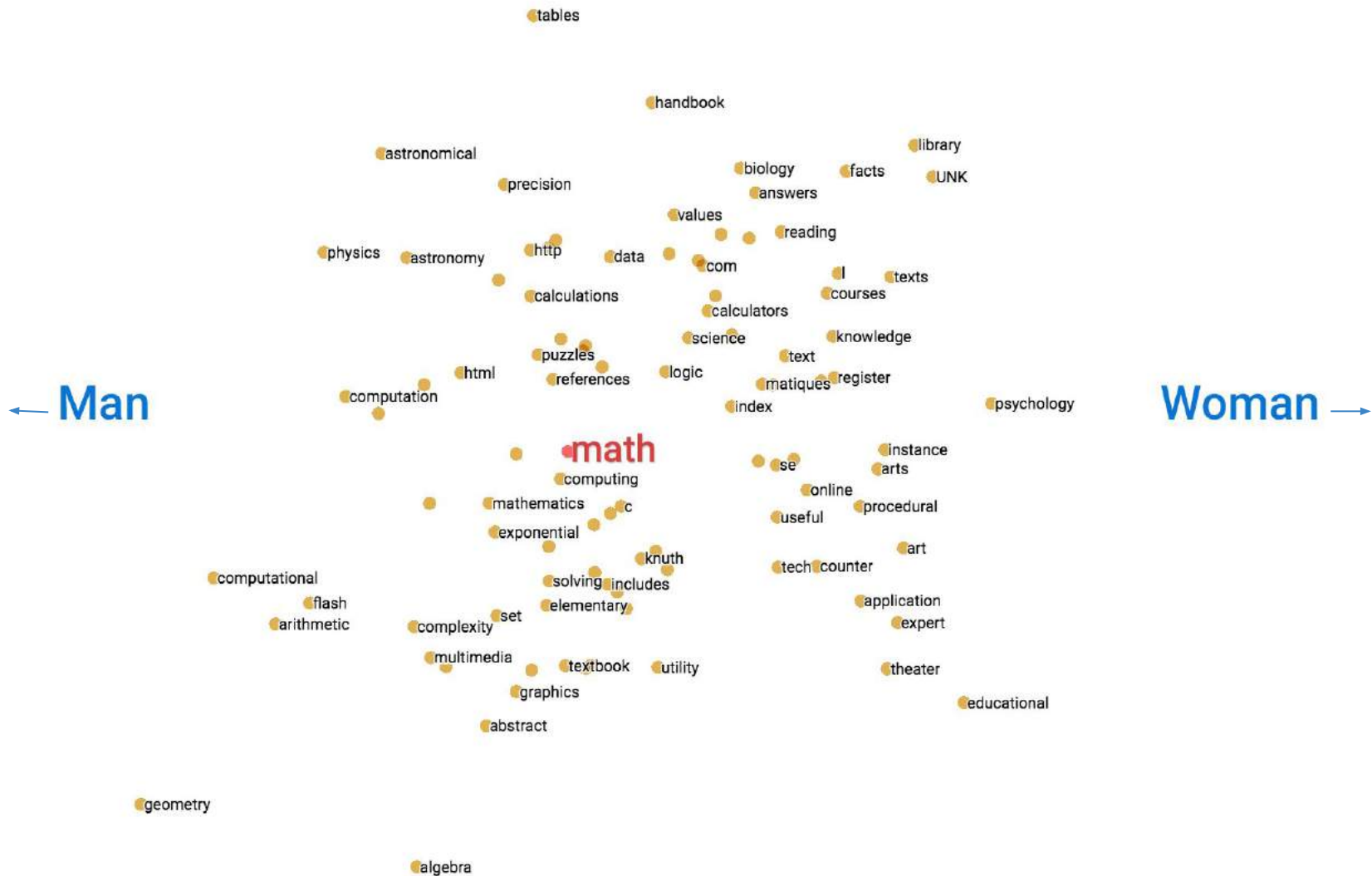
Distributed Representations of Words  
and Phrases and their Compositionality  
Mikolov et al. 2013





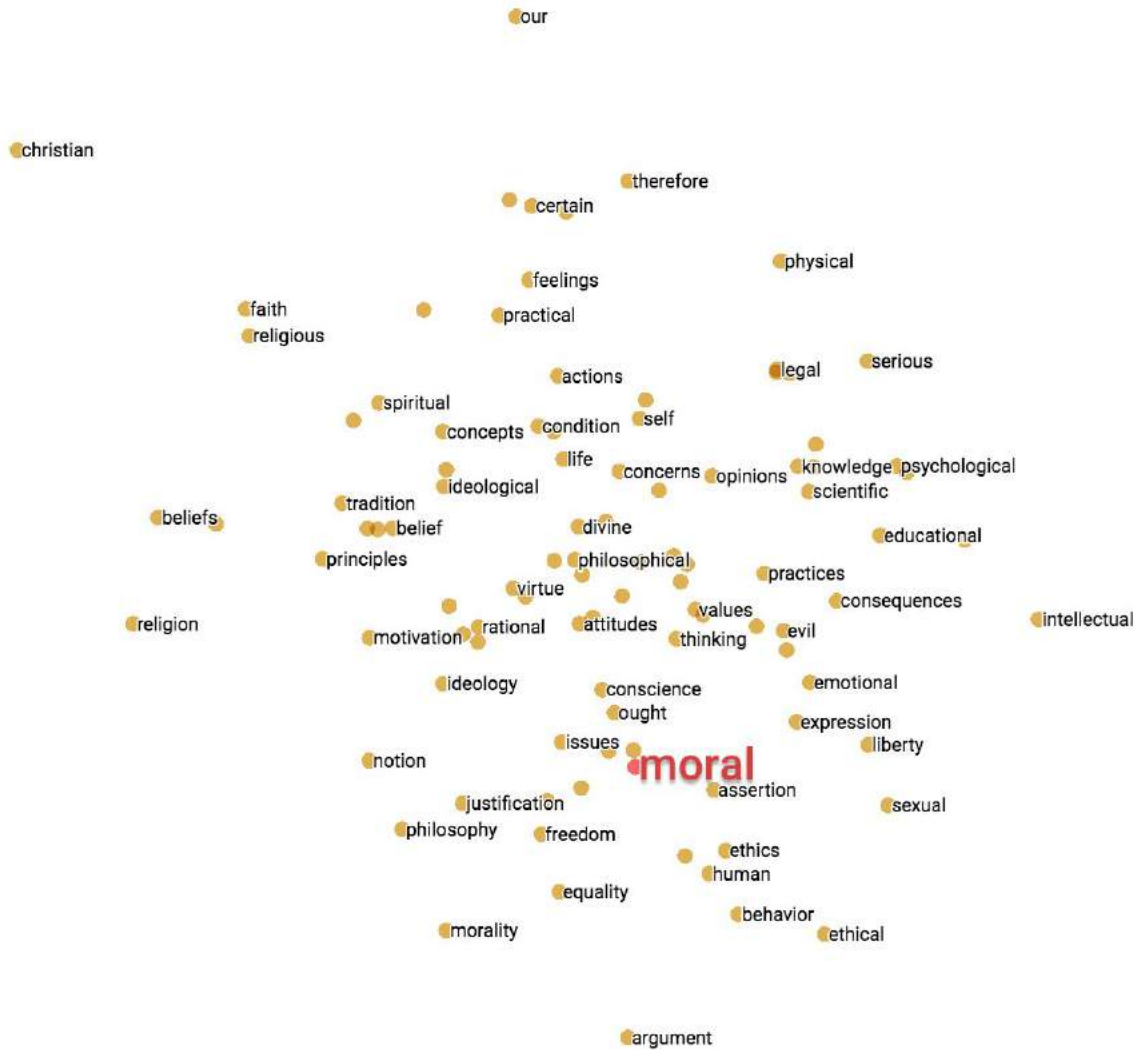




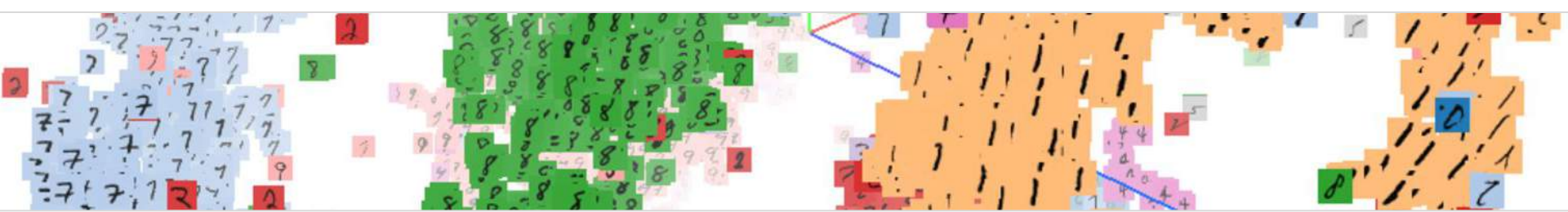


← Christian

Jew →







# Data Visualization for Machine Learning

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google.ai/pair