How have Data Science Skills Evolved? A case study using embeddings

Maryam Jahanshahi Ph.D.
Research Scientist
TapRecruit.co

tapRecruit.co

http://bit.ly/dataengconf2018

TapRecruit uses NLP to understand career content

Converting unstructured documents into structured data

Smart Editor for JDs

Data-driven suggestions on both the content and language use in job descriptions.

Pipeline Health Monitoring

Analytics dashboards to help diagnose quality and diversity issues in talent pipelines.

Salary Estimation

Data-driven salary estimates based on a job's requirements rather than just title and location.

tapRecruit

Search

Account

Job | Sync | Similar Jobs | Open | Large Candidate Pool | Applicants: 202 | 3850 Characters | Notify | Last edit: **System**

28 **Job will perform poorly**

This job scores lower than 95% of **Junior Accounting** jobs in **Los Angeles, CA**

- Add preferred qualifications
- Add more "you" statements
- Perks included
- Equal opportunity statement is included

Neutral — Gendered

Senior Finance Analyst

TapRecruit - Los Angeles

$76,300 BETA

$65,200 — $98,600

TapRecruit is looking for a smart, detail-oriented person to serve as a senior financial analyst. This person will be responsible for supporting the company's FP&A requirements. Responsibilities will include working on TapRecruit Entertainment Group's FP&A model, supporting analysis for long-term planning options, tracking key business operational metrics and producing monthly financial/operation itional FP&A needs, this role will require strong organizational skills to help manage the uide discussions with senior managers across the department and evaluate/implem ojects for top management. This is a dynamic role that serves the finance de report to a Senior Manager of Finance and will routinely interface with TapRecruit's top ma

Language that emphasizes an "intense" or "confusing" environment is known to deter qualified candidates.

Delete

This is an ideal position for an individual who has gained strong investment bank or accounting firm and now seeks to apply those skills to a fast-growing entrepreneurial company. Strong quantitative and excel financial modeling skills are a must. The ideal candidate must be comfortable in a dynamic start-up environment, will bring energy and passion to everything he/she does, and will not be afraid to roll up his/her sleeves to tackle challenging analytical assignments.

This job is full-time, based in Los Angeles. We offer competitive compensation and stock option program.

Language matters in job descriptions

Same title,
Different job

Finance Manager **Kraft Foods**	**Finance Manager** **Roche**
Junior (3 Years)	Senior (6-8 Years)
No Managerial Experience	Division Level Controller
	Strategic Finance Role
	MBA / CPA

Same Title

- Required Experience
- Required Responsibility
- Preferred Skill
- Required Education

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Different title, Same job

Performance Marketing Manager **PocketGems**	**Senior Analyst, Customer Strategy** **The Gap**	
Mid-Level	Mid-Level	**Required Experience**
Quantitative Focus	Quantitative Focus	**Required Skills**
iBanking Expertise	Finance Expertise	**Required Experience**
Data Analysis Tools (SQL)	Relational Database Experience	**Required Skills**
Consulting Experience Preferred	External Consulting Experience Preferred	**Preferred Experience**
MBA Preferred	BA in Accounting, Finance, MBA Preferred	**Preferred Education**

How have data science skills changed over time?

Strategies to identify changes within datasets

MBA	SQL
PhD	Tableau
Python	PowerBI

Manual Feature Extraction:
Require *a priori* selection of key attributes, therefore difficult to discover new attributes

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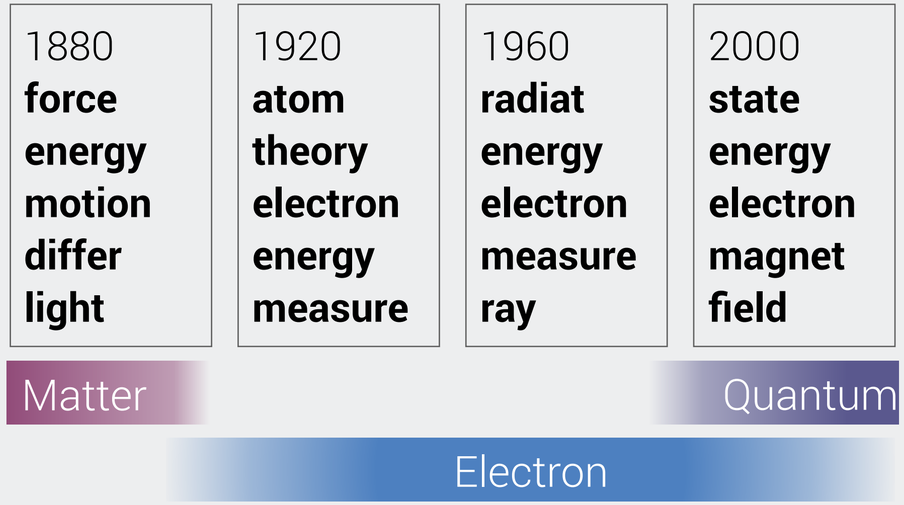

Manual Feature Extraction:
Require *a priori* selection of key attributes, therefore difficult to discover new attributes

Dynamic Topic Models:
Uses a bag of words approach, and require experimentation with topic number.

Adapted from Blei and Lafferty, ICML 2006.

Word embeddings capture semantic similarities

Statistical modeling through software (e.g. SPSS) or programming language (e.g. **Python**)

Context **Word**

Experience in **Python**, Java or other object-oriented programming languages

Context **Word** **Context**

Proficiency programming in **Python**, Java or C++.

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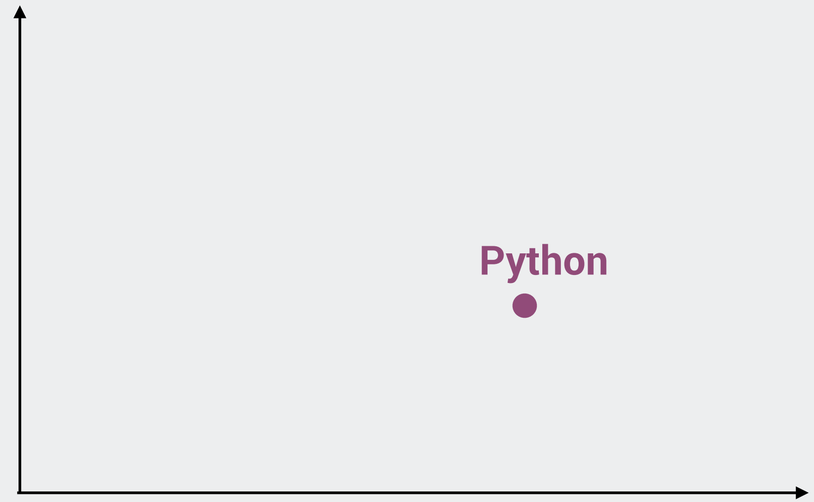

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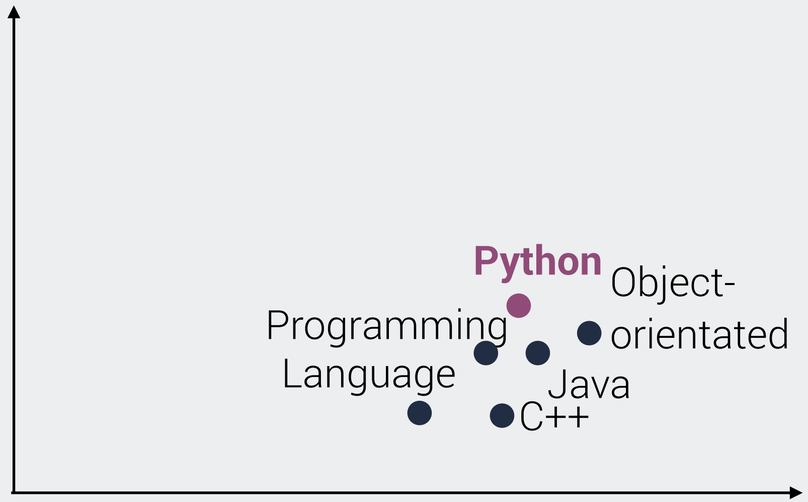

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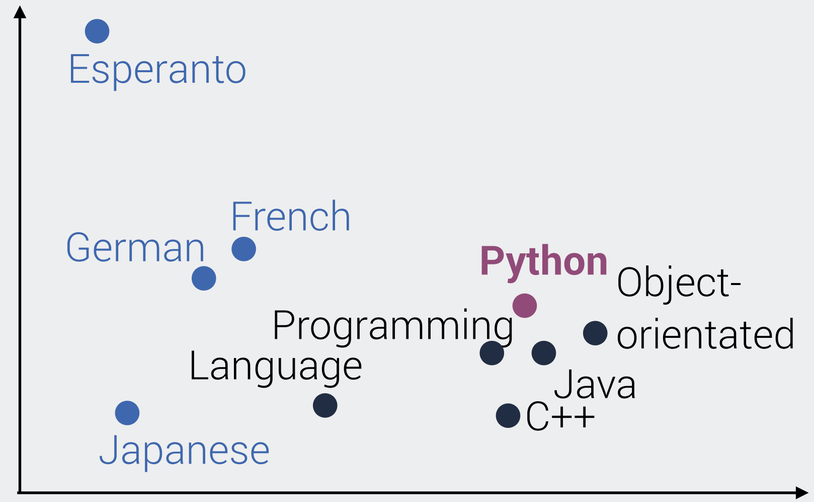
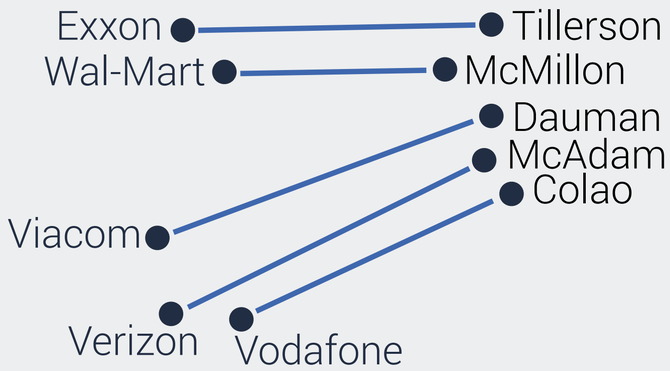


Embeddings capture entity relationships

Dimensionality enables comparison between word pairs along many axes



Hierarchies

Adapted from Stanford NLP GLoVE Project

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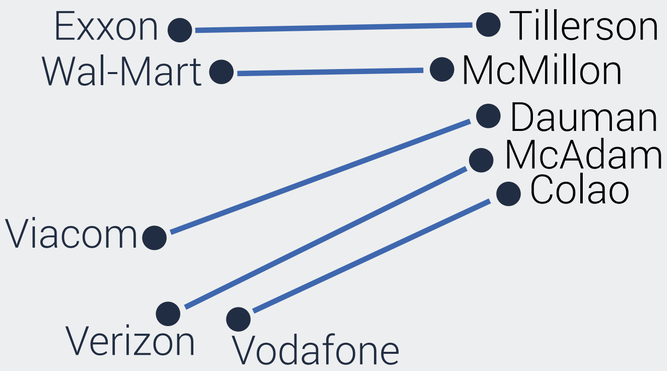

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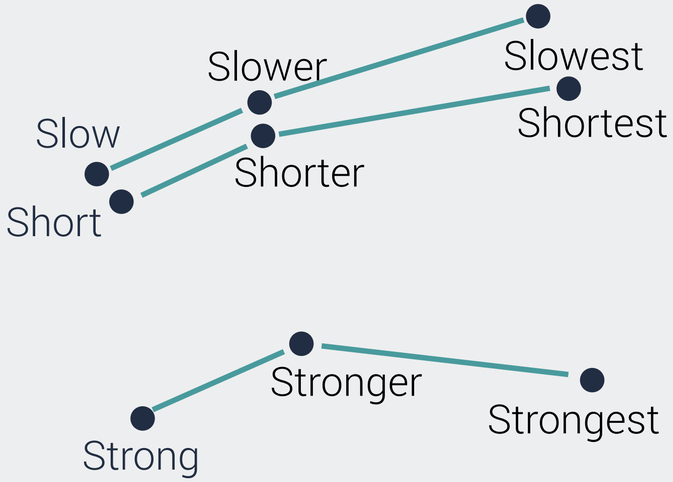

Comparatives and Superlatives

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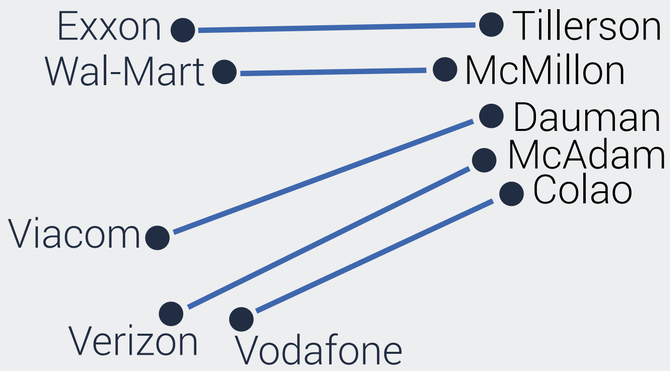

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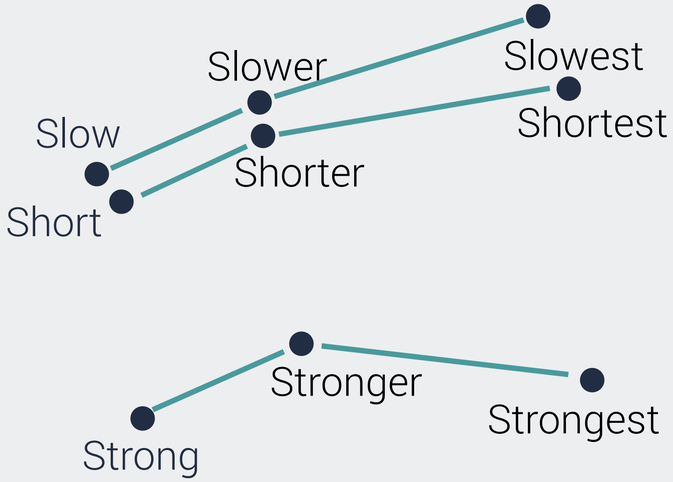

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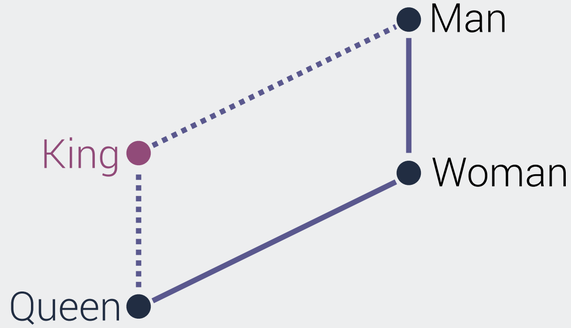
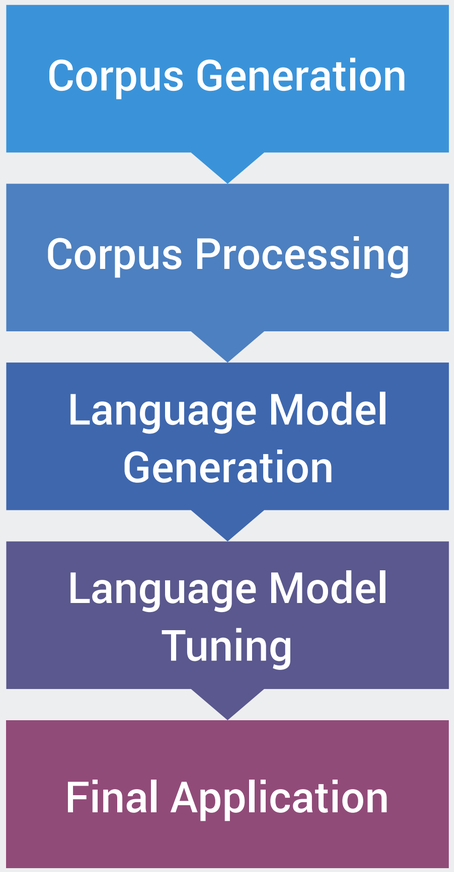


Woman :: Queen as Man :: ?

Adapted from Stanford NLP GLoVE Project

Pretrained embeddings facilitate fast prototyping



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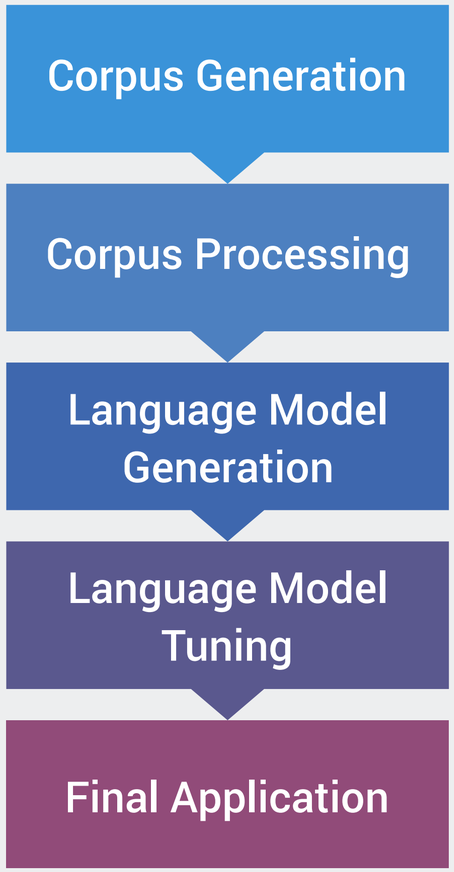


Corpus	Twitter	Common Crawl	GoogleNews	Wikipedia
Tokens	27 B	42-840 B	100 B	6 B
Vocabulary Size	1.2 M	1.9-2.2 M	3 M	400 k
Algorithm	GLoVE	GLoVE	word2vec	GLoVE
Vector Length	25 - 200 d	300 d	300 d	50 - 300 d

Problems with pretrained embedding models

Casing	Abbreviations vs Words e.g. IT vs it
Out of Vocabulary Words	Domain Specific Words & Acronyms
Polysemy	Words with multiple meanings e.g. drive (a car) vs drive (results) e.g. Chef (the job) vs Chef (the language)
Multi-word Expressions	Phrases that have new meanings e.g. Front-end vs front + end

Tools for developing custom language models

Modularized for different data and modeling requirements

spaCy

OPEN NLP™

CoreNLP

SyntaxNet

gensim

PYTORCH

TensorFlow

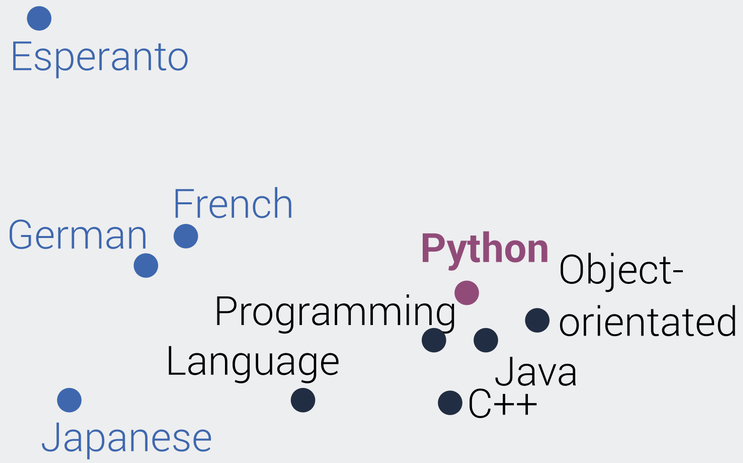
Amazon SageMaker

Corpus Processing
Tokenization, POS tagging, Sentence Segmentation, Dependency Parsing

Language Modeling
Different word embedding models (GLoVE, word2vec, fastText)

Hyperparameter tuning on final model outputs

Window sizes capture semantic similarity vs semantic relatedness

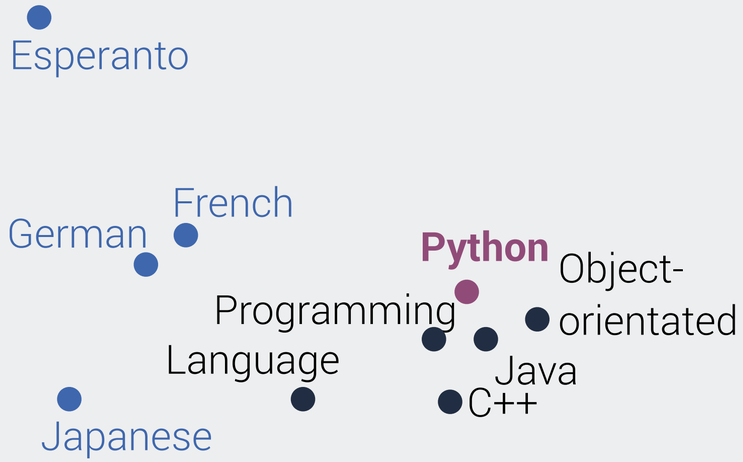


Small Window Size

Capture Semantic similarity,
Substitutes and Word-level differences

Hyperparameter tuning on final model outputs

Window sizes capture semantic similarity vs semantic relatedness



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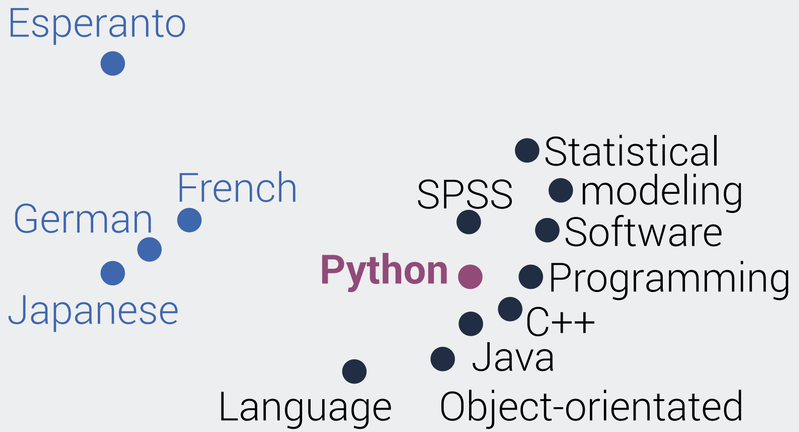
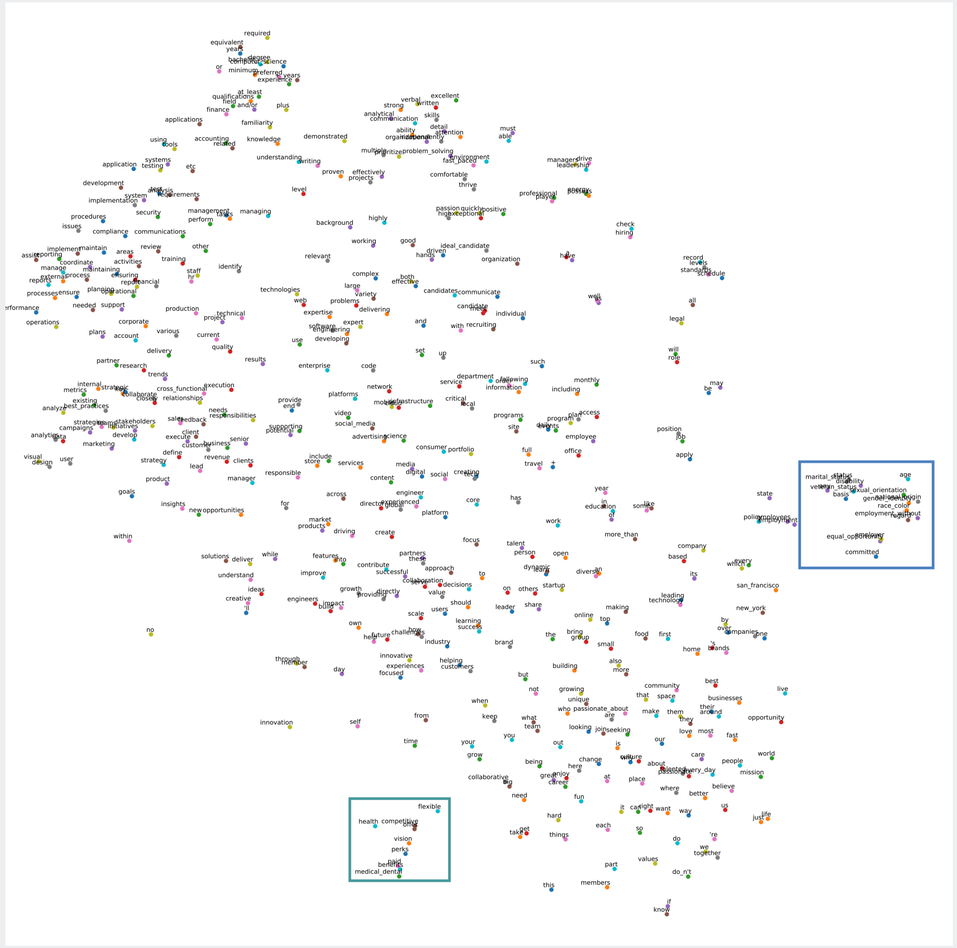


Large Window Size

Capture Semantic relatedness,
Alternatives and Domain-level differences

Career language embedding model

Identified equal opportunity and perks language



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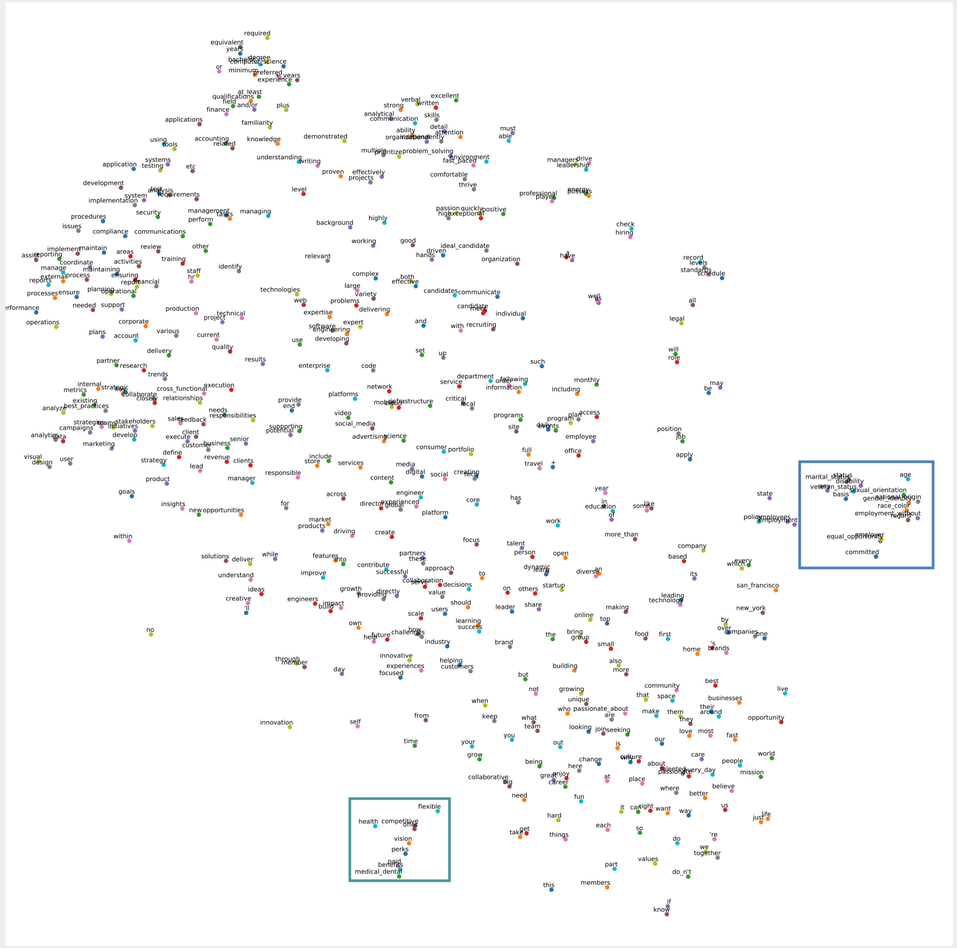

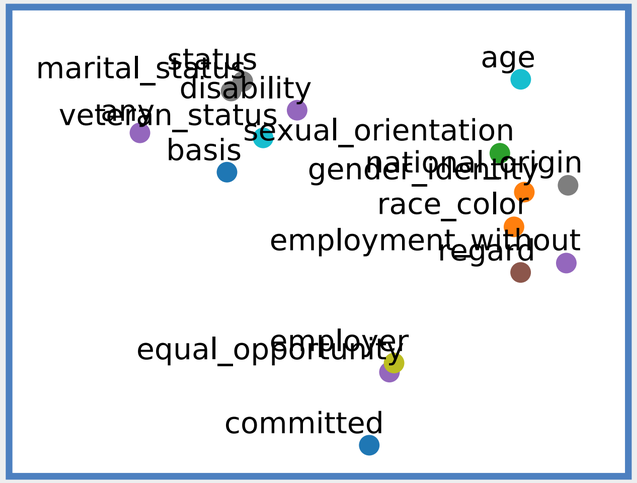

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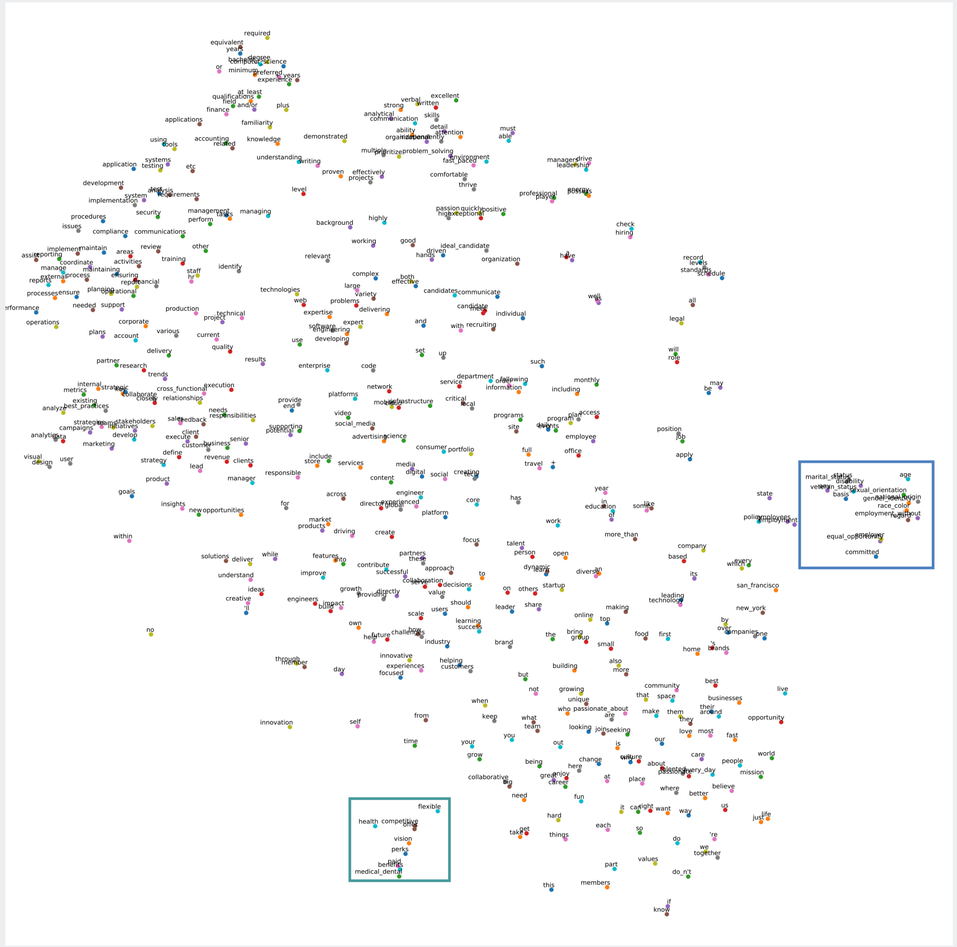

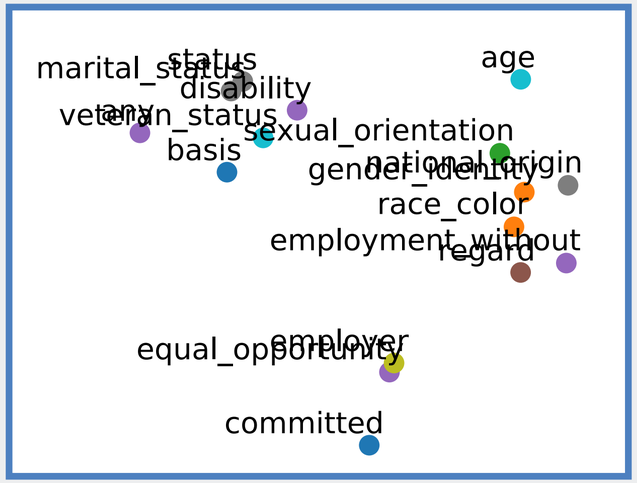

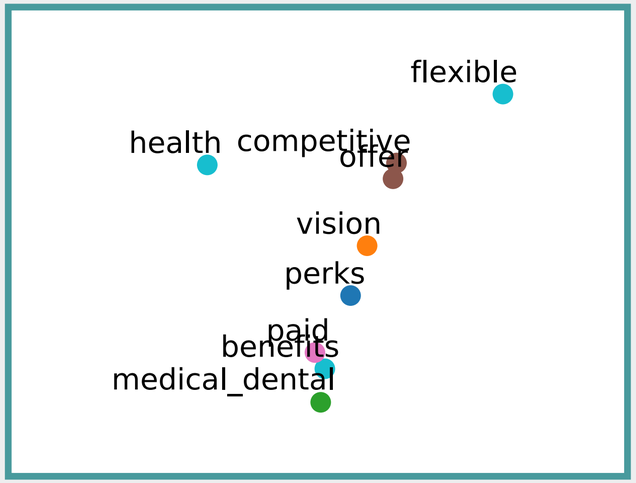

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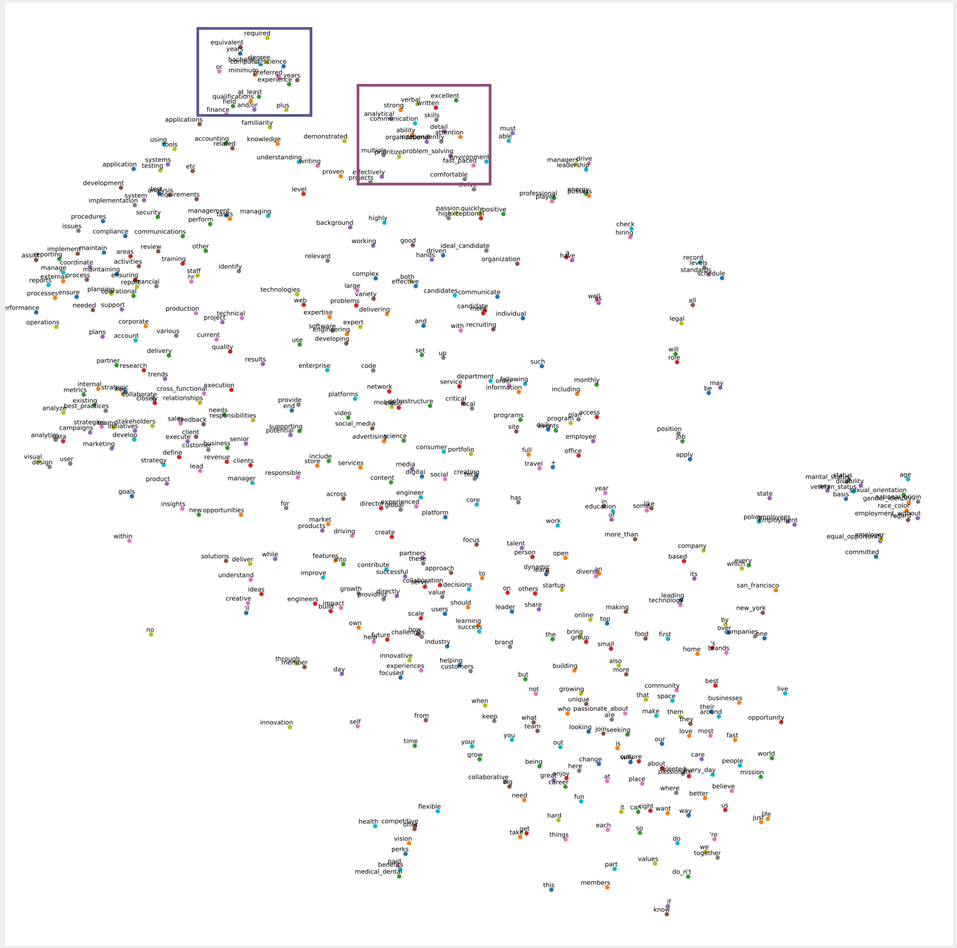
Career language embedding model

Identified 'soft' skills and language around experience



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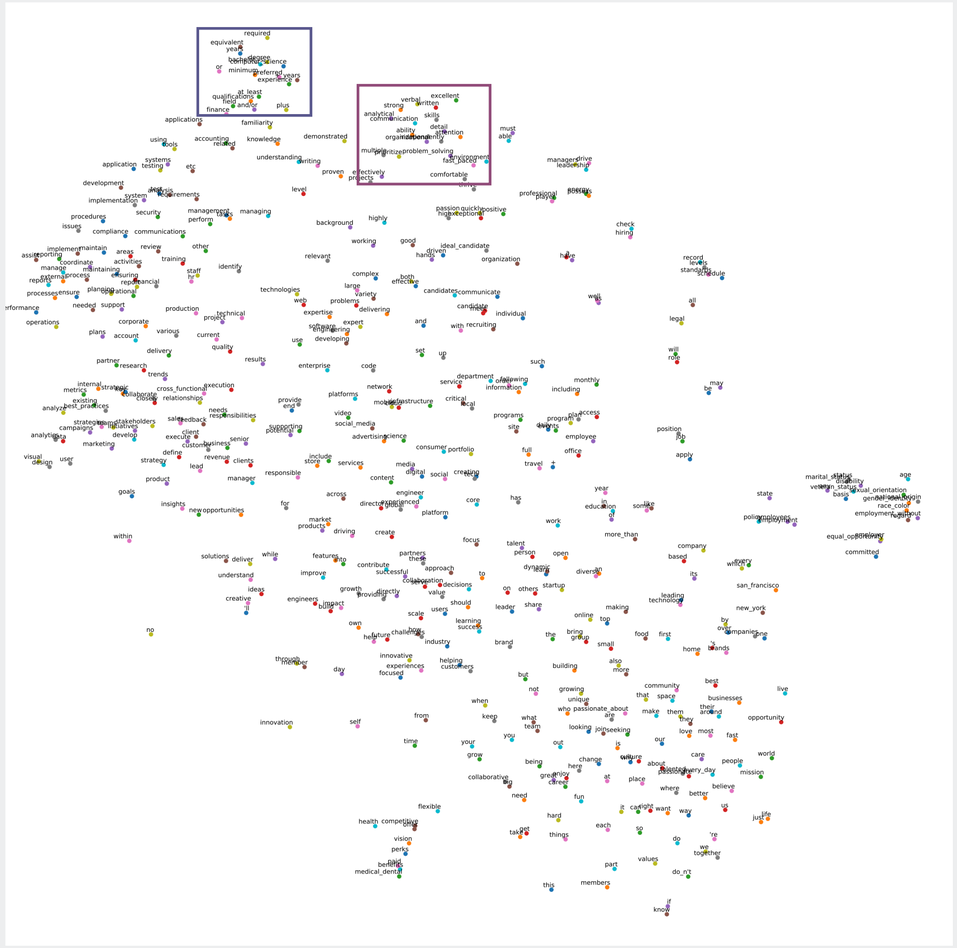
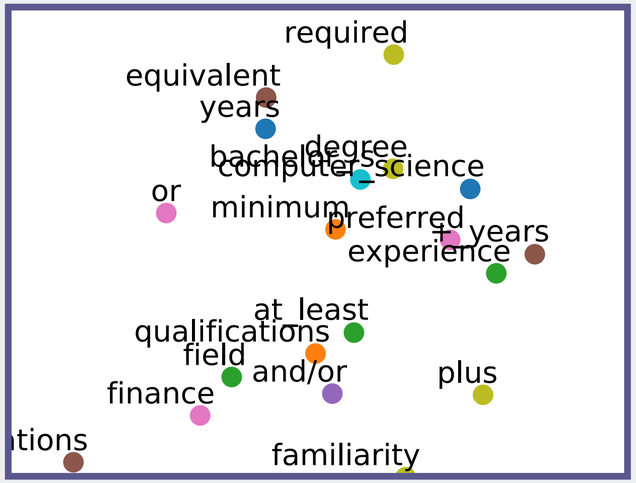
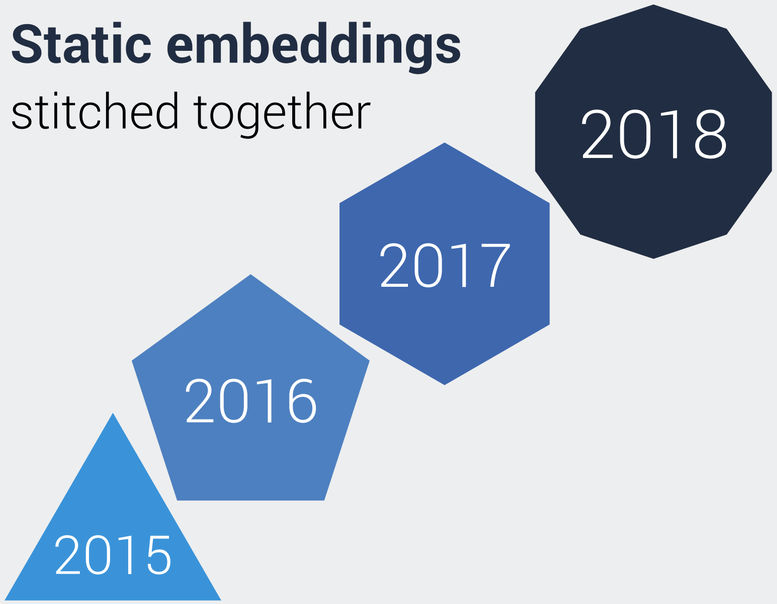




I’ve got 300 dimensions…
but time ain’t one

Two approaches to connect embeddings

Static embeddings
stitched together



Dynamic embeddings
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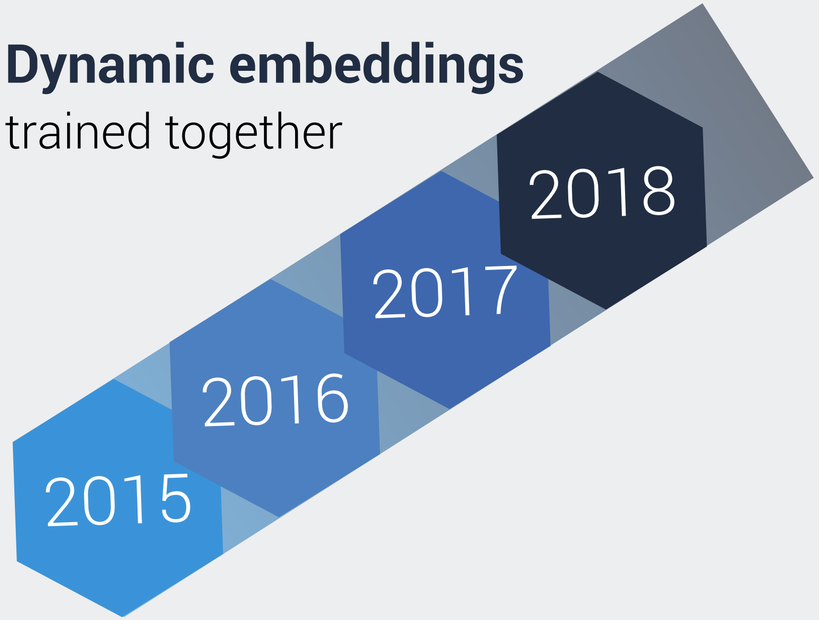

Kim, Chiu, Kaneki, Hedge and Petrov, arXiv: 1405:3515.
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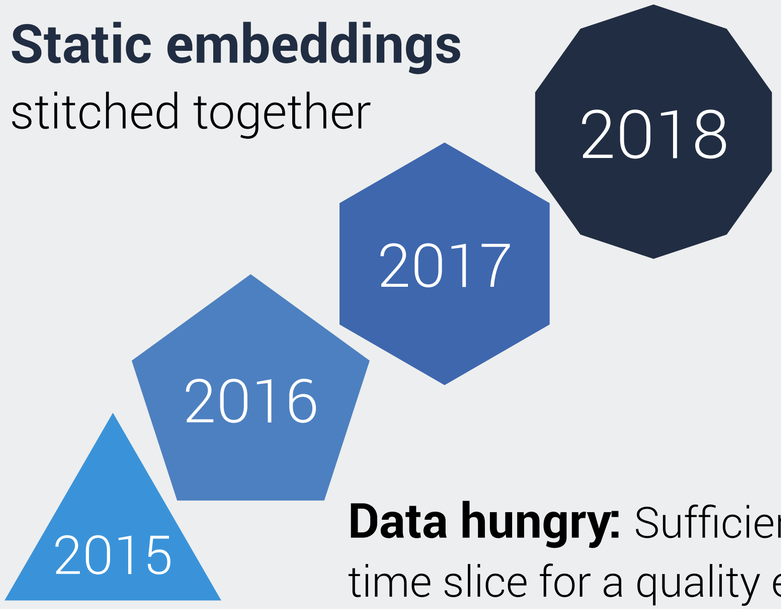

Data hungry: Sufficient data for each time slice for a quality embedding.

Requires alignment: Each time slice is trained independently, therefore dimensions are not comparable across slices.

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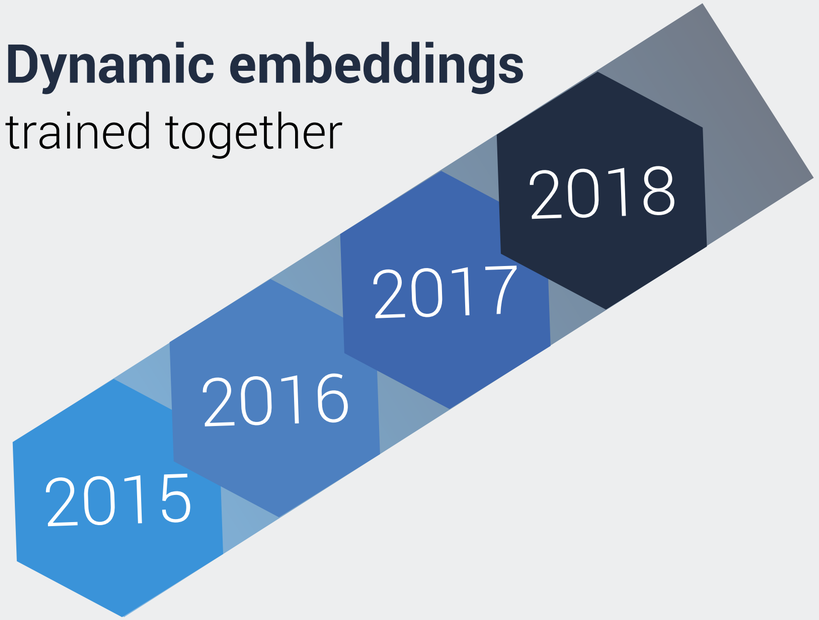

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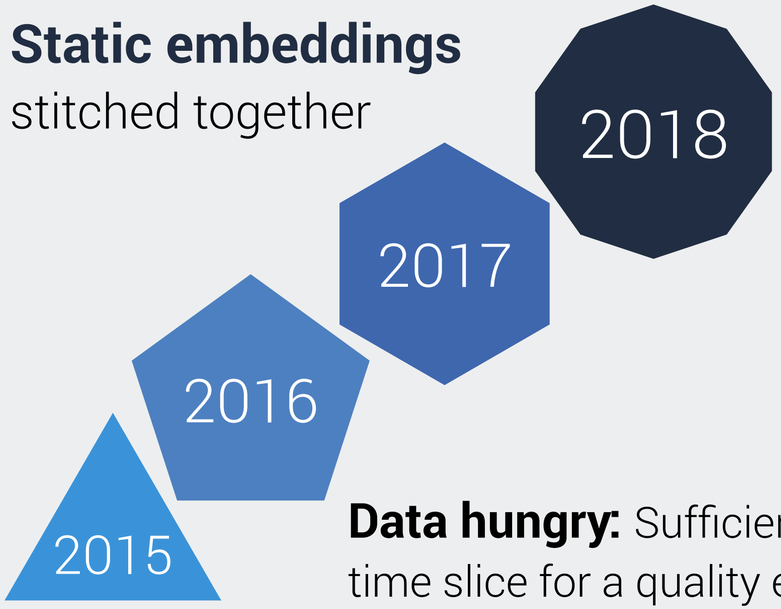

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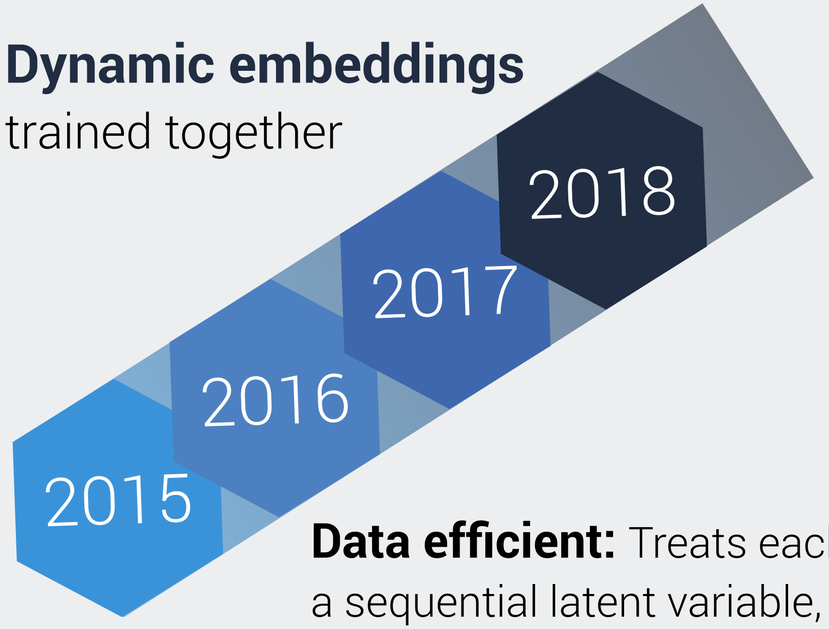

Data efficient: Treats each time slice as a sequential latent variable, enabling time slices with sparse data.

Does not require alignment: Treating time slice as a variable ensures embeddings are connected across slices.

Balmer and Mandt, arXiv: 1702:08359
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Dynamic embeddings models

Rudolph and Blei, arXiv: 1703:08052

Absolute drift

Identifies top words whose usage changes over time course

words with largest drift (Senate)			
IRAQ	3.09	coin	2.39
tax cuts	2.84	social security	2.38
health care	2.62	FINE	2.38
energy	2.55	signal	2.38
medicare	2.55	program	2.36
DISCIPLINE	2.44	moves	2.35
text	2.41	credit	2.34
VALUES	2.40	UNEMPLOYMENT	2.34

Embedding neighborhoods

Extract semantic changes by nearest neighbors of drifting words

UNEMPLOYMENT		
1858	**1940**	**2000**
unemployment	unemployment	unemployment
unemployed	unemployed	jobless
depression	depression	rate
acute	alleviating	depression
deplorable	destitution	forecasts
alleviating	acute	crate
destitution	reemployment	upward
urban	deplorable	lag
employment	employment	economists
distressing	distress	predict

Repository Link: http://bit.ly/dyn_bern_emb

Experiments with Dynamic Bernoulli Embeddings

	Small Corpus	Large Corpus
Job Types	All	All
Time Slices	3 (2016-2018)	3 (2016-2018)
Number of Documents	**50 k**	**500 k**
Vocabulary Size	10 k	10 k
Data Preprocessing	Basic	Basic
Embedding Training	100 dimensions, 10 epochs	100 dimensions, 10 epochs

Repository Link: http://bit.ly/dyn_bern_emb

Dynamic Bernoulli embeddings

Small corpus identified gains and losses

Demand for PhDs and MBAs is Falling

PhDs in All Jobs

-23%

PhDs in DS Jobs

-30%

MBAs in All Jobs

-35%

Blue boxes indicate phrases identified from top drifting words analysis.
Grey boxes indicate ‘control’ skills.

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Data Science skills showing significant shifts

Tableau

+20%

PowerBI

+100%

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Spark
Steady

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Hadoop
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MBAs in All Jobs
-35%

Data Science skills showing significant shifts

Tableau	Spark	Python
+20%	Steady	Steady

PowerBI	Hadoop	Perl
+100%	-30%	-40%

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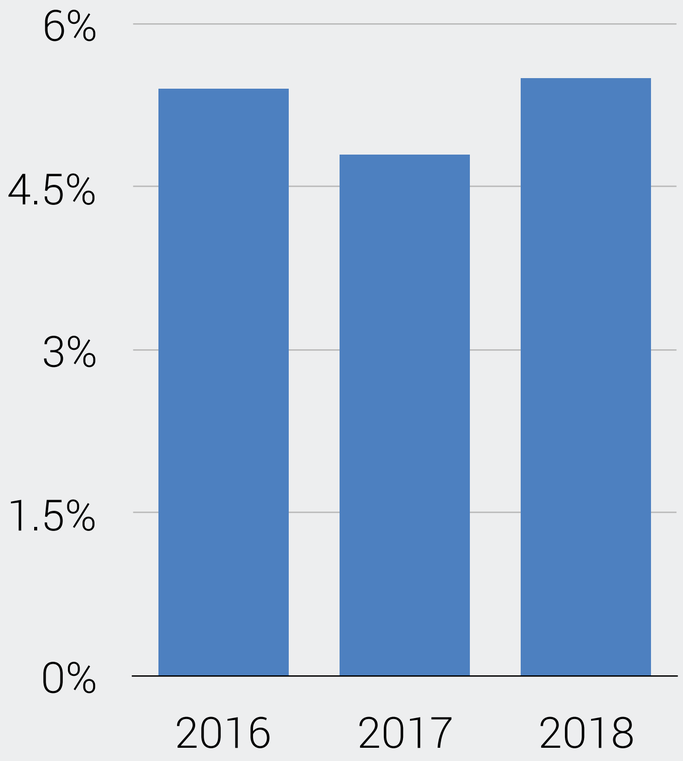
Dynamic Bernoulli embeddings

Large corpus identified role-type dependent shifts in requirements

No change to SQL demand



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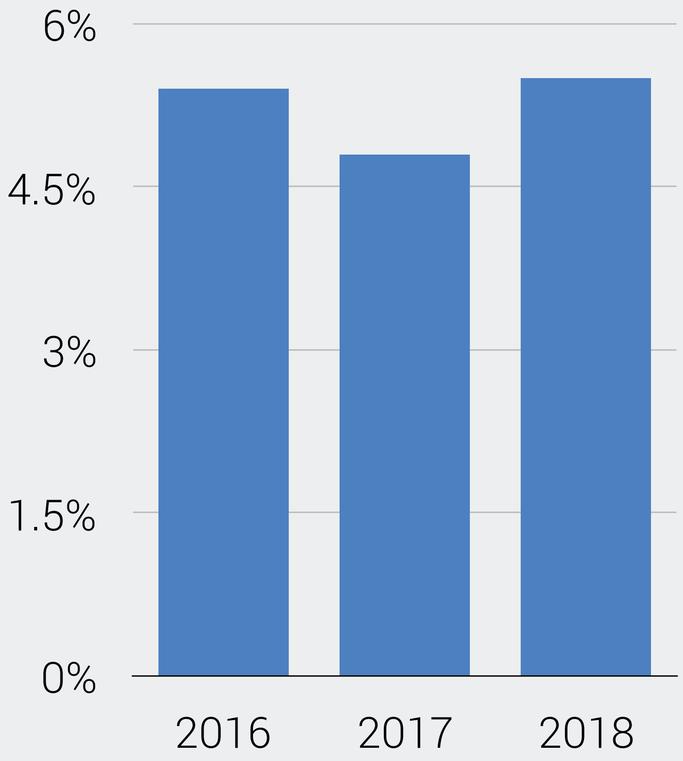

SQL requirement increases in specific functions

FP&A Roles **+70%**	Sales Roles **Steady**	Marketing Roles **Steady**
FinTech Roles **Steady**	BizDev Roles **+50%**	HR Roles **+25%**

regression :: Generalized Linear Models as word2vec :: Exponential Family Embeddings

Exponential Family Embeddings

Conditional probabilistic models generalize the spirit of embeddings to other data types

	Proficiency
Context	programming
	Python
Datapoint	**Java**
Context	C++

Bernoulli Embeddings

Binary Data

Presence of word, given surrounding words

Adapted from Rudolph, Ruiz, Mandt and Blei, arXiv: 1608.00778.

Exponential Family Embeddings

Conditional probabilistic models generalize the spirit of embeddings to other data types

	Proficiency
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Bernoulli Embeddings

Binary Data

Presence of word, given surrounding words

	Mini Bagels
Context	Cream cheese
	Milk
Datapoint	**Coffee**
Context	Orange Juice

Poisson Embeddings

Count or Ordinal Data

Number of item purchased, given number of other items purchased in the same cart.

Adapted from Rudolph, Ruiz, Mandt and Blei, arXiv: 1608.00778.

Exponential Family Embeddings

Conditional probabilistic models generalize the spirit of embeddings to other data types

	Proficiency
Context	programming
	Python
Datapoint	**Java**
Context	C++

Bernoulli Embeddings

Binary Data

Presence of word, given surrounding words

	Mini Bagels
Context	Cream cheese
	Milk
Datapoint	**Coffee**
Context	Orange Juice

Poisson Embeddings

Count or Ordinal Data

Number of item purchased, given number of other items purchased in the same cart.

	JFK-CDG
Context	LGA-DCA
	JFK-DFW
Datapoint	**LAX-JFK**
Context	LAX-LGA

Gaussian Embeddings

Continuous Data

Weight of an edge, given other edges on the same node.

Adapted from Rudolph, Ruiz, Mandt and Blei, arXiv: 1608.00778.

Exponential Family Embeddings

Poisson embeddings capture item similarities from shopper behavior

	Mini Bagels
Context	Cream cheese
	Milk
Datapoint	**Coffee**
Context	Orange Juice

Poisson Embeddings

Count or Ordinal Data

Adapted from Rudolph, Ruiz, Mandt and Blei, arXiv: 1608.00778.

Exponential Family Embeddings

Poisson embeddings capture item similarities from shopper behavior

	Mini Bagels	**262**
Context	Cream cheese	223
	Milk	162
Datapoint	**Coffee**	137
Context	Orange Juice	
		293
Poisson Embeddings		69
Count or Ordinal Data		176
		241

Adapted from Rudolph, Ruiz, Mandt and Blei, arXiv: 1608.00778.

Exponential Family Embeddings

Poisson embeddings capture item similarities from shopper behavior

	Mini Bagels	**262**	**Maruchan chicken ramen**
Context	Cream cheese	223	Maruchan creamy chicken ramen
	Milk	162	Maruchan oriental flavor ramen
Datapoint	**Coffee**	137	Maruchan roast chicken ramen
Context	Orange Juice		
		293	**Yoplait strawberry yogurt**
Poisson Embeddings		69	Yoplait apricot mango yogurt
Count or Ordinal Data		176	Yoplait strawberry orange smoothie
		241	Yoplait strawberry banana yogurt

Adapted from Rudolph, Ruiz, Mandt and Blei, arXiv: 1608.00778.

Exponential Family Embeddings

Inner product of vectors identify substitutes and alternatives

High Inner Product Combinations:
Yield products that are frequently bought together

Old Dutch potato chips & Budweiser Lager beer

Lays potato chips & DiGiorno frozen pizza

Adapted from Rudolph, Ruiz, Mandt and Blei, arXiv: 1608.00778.

Exponential Family Embeddings

Inner product of vectors identify substitutes and alternatives

High Inner Product Combinations:
Yield products that are frequently bought together

Old Dutch potato chips & Budweiser Lager beer

Lays potato chips & DiGiorno frozen pizza

Low Inner Product Combinations:
Yield products that are rarely bought together

General Mills cinnamon toast & Tide Plus detergent

Beef Swanson Broth soup & Campbell Soup cans

Adapted from Rudolph, Ruiz, Mandt and Blei, arXiv: 1608.00778.

How have data science skills changed over time?

How have data science skills changed over time?

- Flavors of static word embeddings: The Corpus Issue
- Considerations for developing custom embedding models
- Flavors of dynamic models: Dynamic Bernoulli embeddings
- Other members of the Exponential Family of Embeddings

Thank you DataEngConf!

Maryam Jahanshahi Ph.D.
Research Scientist
@mjahanshahi
maryam-j

tapRecruit.co

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