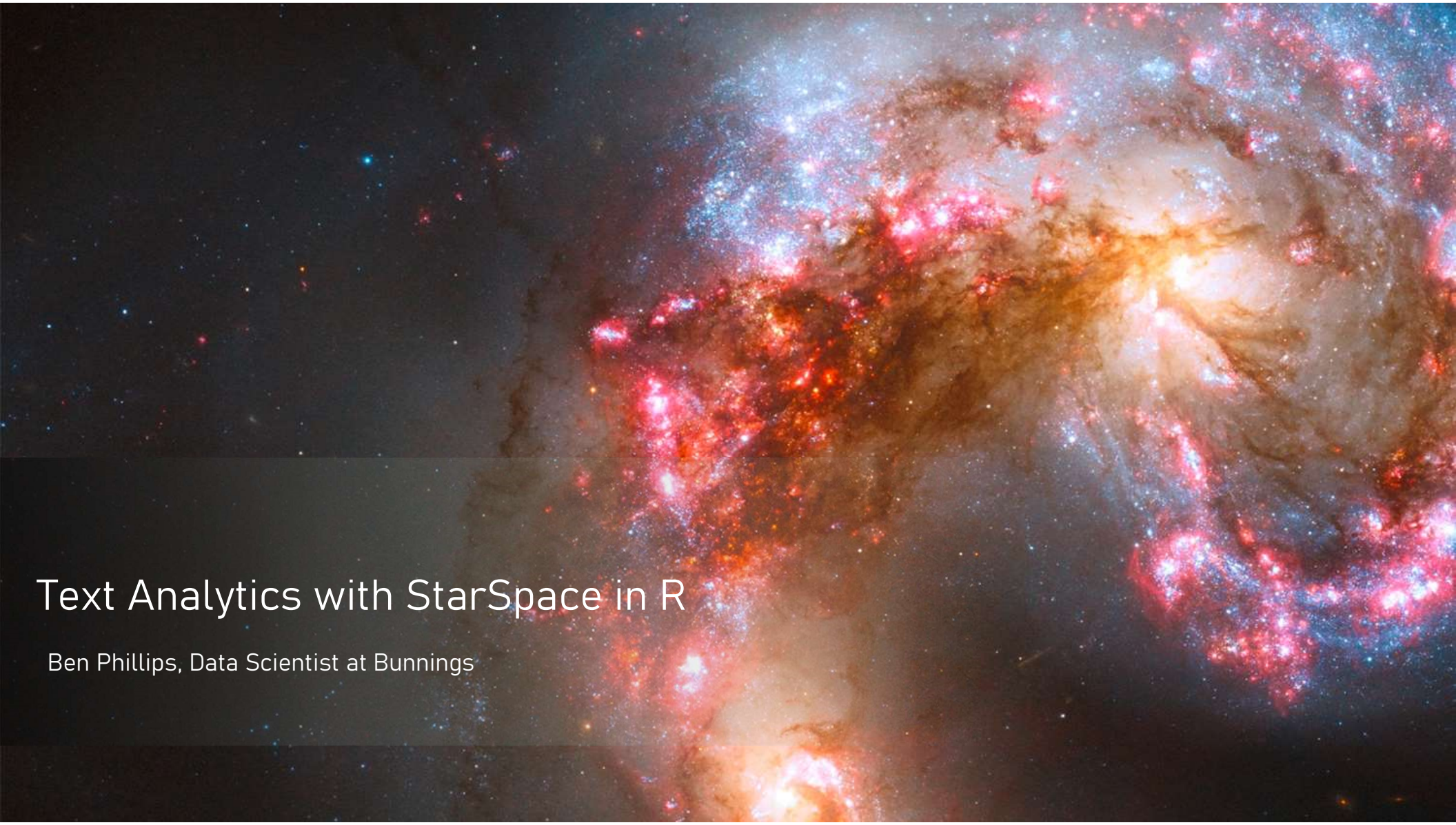


Text Analytics with StarSpace in R

Ben Phillips, Data Scientist at Bunnings

About Me

- Benjamin.phillips22@gmail.com
- Benjaminphillips22.github.io

Project Euler.net

About Project Euler

What is Project Euler?

Project Euler is a series of challenging mathematical/computer programming problems that will require more than just mathematical insights to solve. Although mathematics will help you arrive at elegant and efficient methods, the use of a computer and programming skills will be required to solve most problems.

The motivation for starting Project Euler, and its continuation, is to provide a platform for the inquiring mind to delve into unfamiliar areas and learn new concepts in a fun and recreational context.

Who are the problems aimed at?

The intended audience include students for whom the basic curriculum is not feeding their hunger to learn, adults whose background was not primarily mathematics but had an interest in things mathematical, and professionals who want to keep their problem solving and mathematics on the cutting edge.

Can anyone solve the problems?

The problems range in difficulty and for many the experience is inductive chain learning. That is, by solving one problem it will expose you to a new concept that allows you to undertake a previously inaccessible problem. So the determined participant will slowly but surely work his/her way through every problem.

Project Euler.net

Special Pythagorean triplet

Problem 9

A Pythagorean triplet is a set of three natural numbers, $a < b < c$, for which,

$$a^2 + b^2 = c^2$$

For example, $3^2 + 4^2 = 9 + 16 = 25 = 5^2$.

There exists exactly one Pythagorean triplet for which $a + b + c = 1000$.
Find the product abc.


BUNNINGS
warehouse
OPEN
7am
hire

Product Owner

Data Scientist

Safety Use Case

Data Engineer

Data Scientist/
Business Translator

Initial situation.

Data on safety incidents.

Where we want to be.

Descriptive analytics.

- Do the incidents fall into broad categories?
- What are the characteristics of those categories?

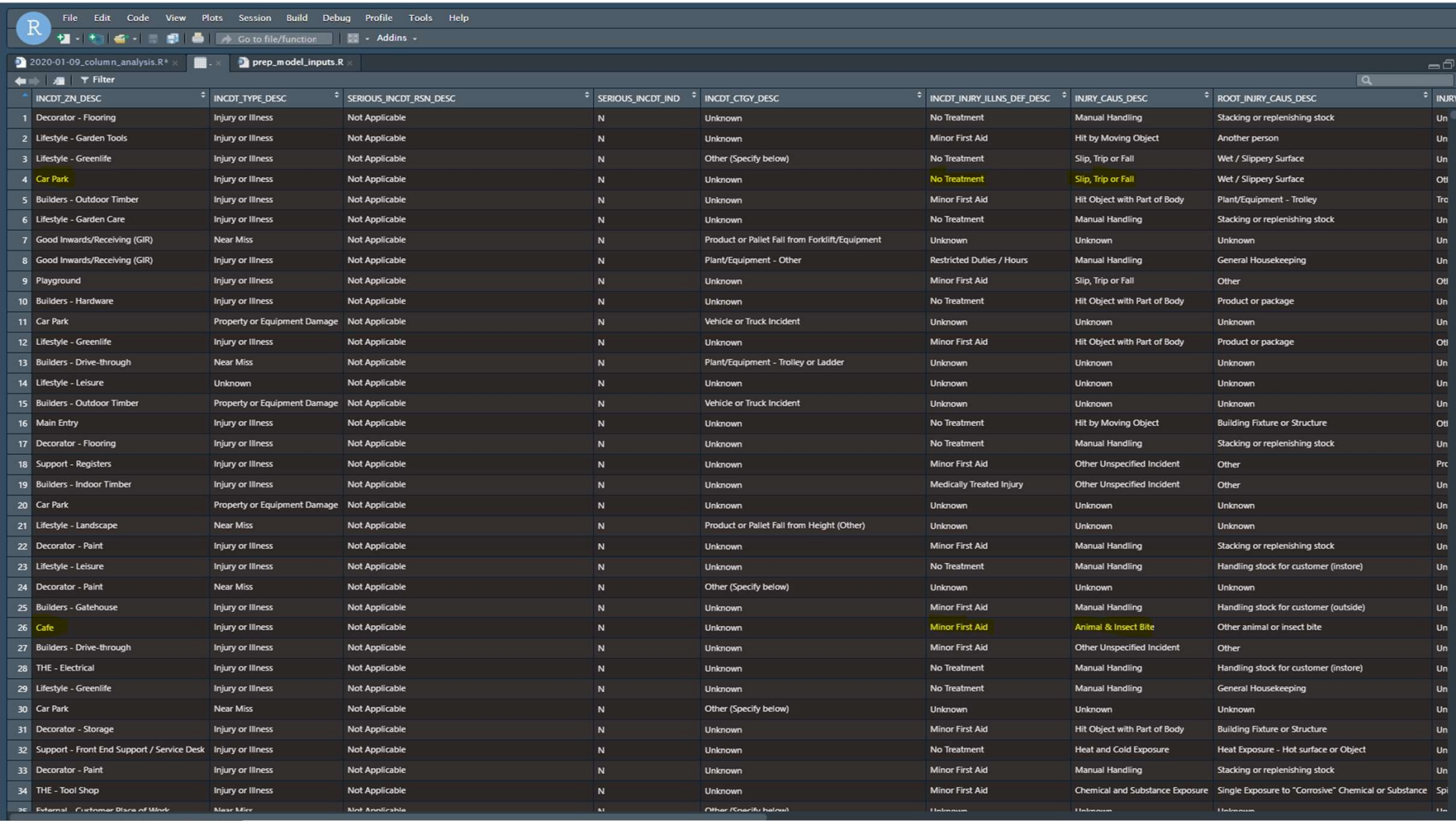
Data

"while working with another team member to put shade cloth away it was difficult to maneuver..."

"was placing items on shelf when a nearby item fell and broke on the ground..."

"tm was walking in the yard there was a big gust of wind this created a small dust storm which went into his eyes....."

"tm went to lift a gas bottle when a bee fly and..."

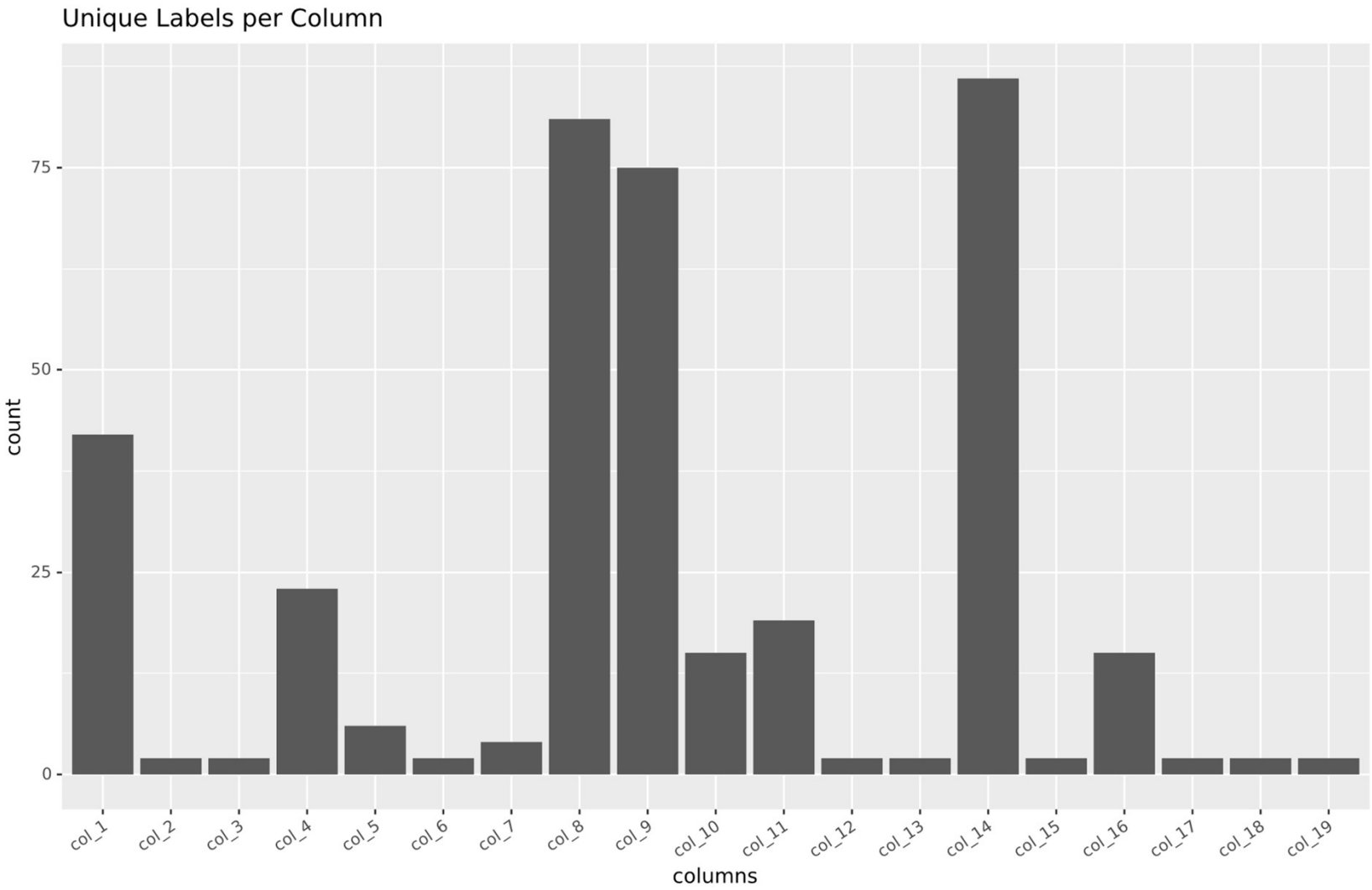

File Edit Code View Plots Session Build Debug Profile Tools Help

Go to file/function | Addins

2020-01-09_column_analysis.R* | prep_model_inputs.R

Filter

	INCDT_ZN_DESC	INCDT_TYPE_DESC	SERIOUS_INCDT_RSN_DESC	SERIOUS_INCDT_IND	INCDT_CTGY_DESC	INCDT_INJRY_ILLNS_DEF_DESC	INJRY_CAUS_DESC	ROOT_INJRY_CAUS_DESC	INJR
1	Decorator - Flooring	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Manual Handling	Stacking or replenishing stock	Un
2	Lifestyle - Garden Tools	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Hit by Moving Object	Another person	Un
3	Lifestyle - Greenlife	Injury or Illness	Not Applicable	N	Other (Specify below)	No Treatment	Slip, Trip or Fall	Wet / Slippery Surface	Un
4	Car Park	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Slip, Trip or Fall	Wet / Slippery Surface	Otl
5	Builders - Outdoor Timber	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Hit Object with Part of Body	Plant/Equipment - Trolley	Tro
6	Lifestyle - Garden Care	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Manual Handling	Stacking or replenishing stock	Un
7	Good Inwards/Receiving (GIR)	Near Miss	Not Applicable	N	Product or Pallet Fall from Forklift/Equipment	Unknown	Unknown	Unknown	Un
8	Good Inwards/Receiving (GIR)	Injury or Illness	Not Applicable	N	Plant/Equipment - Other	Restricted Duties / Hours	Manual Handling	General Housekeeping	Un
9	Playground	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Slip, Trip or Fall	Other	Otl
10	Builders - Hardware	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Hit Object with Part of Body	Product or package	Un
11	Car Park	Property or Equipment Damage	Not Applicable	N	Vehicle or Truck Incident	Unknown	Unknown	Unknown	Un
12	Lifestyle - Greenlife	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Hit Object with Part of Body	Product or package	Otl
13	Builders - Drive-through	Near Miss	Not Applicable	N	Plant/Equipment - Trolley or Ladder	Unknown	Unknown	Unknown	Un
14	Lifestyle - Leisure	Unknown	Not Applicable	N	Unknown	Unknown	Unknown	Unknown	Un
15	Builders - Outdoor Timber	Property or Equipment Damage	Not Applicable	N	Vehicle or Truck Incident	Unknown	Unknown	Unknown	Un
16	Main Entry	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Hit by Moving Object	Building Fixture or Structure	Otl
17	Decorator - Flooring	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Manual Handling	Stacking or replenishing stock	Un
18	Support - Registers	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Other Unspecified Incident	Other	Pro
19	Builders - Indoor Timber	Injury or Illness	Not Applicable	N	Unknown	Medically Treated Injury	Other Unspecified Incident	Other	Un
20	Car Park	Property or Equipment Damage	Not Applicable	N	Unknown	Unknown	Unknown	Unknown	Un
21	Lifestyle - Landscape	Near Miss	Not Applicable	N	Product or Pallet Fall from Height (Other)	Unknown	Unknown	Unknown	Un
22	Decorator - Paint	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Manual Handling	Stacking or replenishing stock	Un
23	Lifestyle - Leisure	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Manual Handling	Handling stock for customer (instore)	Un
24	Decorator - Paint	Near Miss	Not Applicable	N	Other (Specify below)	Unknown	Unknown	Unknown	Un
25	Builders - Gatehouse	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Manual Handling	Handling stock for customer (outside)	Un
26	Cafe	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Animal & Insect Bite	Other animal or insect bite	Un
27	Builders - Drive-through	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Other Unspecified Incident	Other	Un
28	THE - Electrical	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Manual Handling	Handling stock for customer (instore)	Un
29	Lifestyle - Greenlife	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Manual Handling	General Housekeeping	Un
30	Car Park	Near Miss	Not Applicable	N	Other (Specify below)	Unknown	Unknown	Unknown	Un
31	Decorator - Storage	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Hit Object with Part of Body	Building Fixture or Structure	Un
32	Support - Front End Support / Service Desk	Injury or Illness	Not Applicable	N	Unknown	No Treatment	Heat and Cold Exposure	Heat Exposure - Hot surface or Object	Un
33	Decorator - Paint	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Manual Handling	Stacking or replenishing stock	Un
34	THE - Tool Shop	Injury or Illness	Not Applicable	N	Unknown	Minor First Aid	Chemical and Substance Exposure	Single Exposure to "Corrosive" Chemical or Substance	Spi
35	External - Customer Place of Work	Near Miss	Not Applicable	N	Other (Specify below)	Unknown	Unknown	Unknown	Un


Unique Labels per Column
count
75
50
25
0
col_1
col_2
col_3
col_4
col_5
col_6
col_7
col_8
col_9
col_10
col_11
col_12
col_13
col_14
col_15
col_16
col_17
col_18
col_19
columns

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1,359 likes

#TAGSPACE: Semantic Embeddings from Hashtags

Jason Weston
Facebook AI Research
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Sumit Chopra
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spchopra@fb.com

Keith Adams
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Abstract

We describe a convolutional neural network that learns feature representations for short textual posts using hashtags as a supervised signal. The proposed approach is trained on up to 5.5 billion words predicting 100,000 possible hashtags. As well as strong performance on the hashtag prediction task itself, we show that its learned representation of text (ignoring the hashtag labels) is useful for other tasks as well. To that end, we present results on a document recommendation task, where it also outperforms a number of baselines.

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resented as a vector in $\mathbb{R}^n$, where n is a hyp parameter that controls capacity. The embeddi of words comprising a text are combined usin model-dependent, possibly learned function, p ducing a point in the same embedding space. similarity measure (for example, inner produ gauges the pairwise relevance of points in the e bedding space.

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In this work we develop a convolutional r work for large scale ranking tasks, and apply

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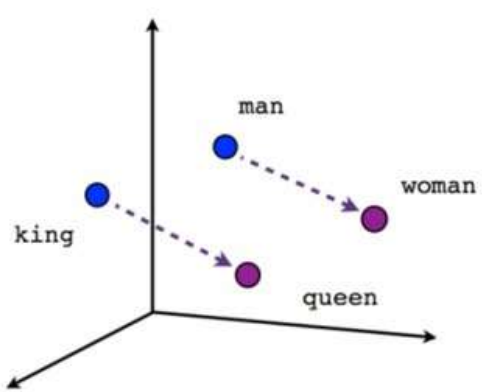
In the domain of recommendation, embedding mo have had a large degree of success, starting from S

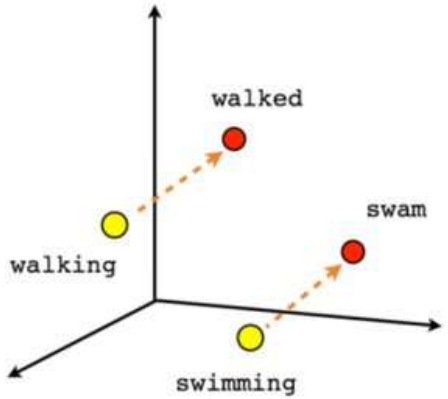
What are Embeddings?

For example

King; [0.02, -0.30, 0.66]
Queen; [0.20, -0.30, 0.55]

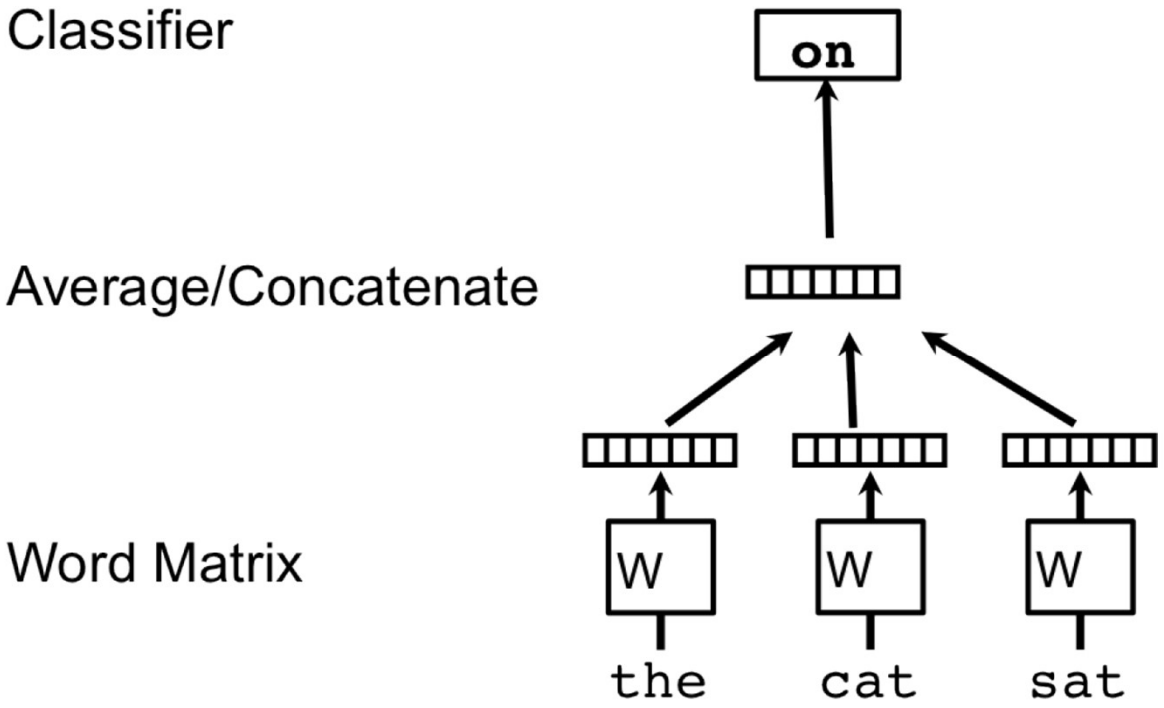


Male-Female



Verb tense

Word Embeddings



GloVe: Global Vectors for Word Representation

Jeffrey Pennington, Richard Socher, Christopher D. Manning

Introduction

GloVe is an unsupervised learning algorithm for obtaining vector representations for words. Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase interesting linear substructures of the word vector space.

Getting started (Code download)

- Download the code (licensed under the Apache License, Version 2.0)
- Unpack the files: unzip GloVe-1.2.zip
- Compile the source: cd GloVe-1.2 && make
- Run the demo script: ./demo.sh
- Consult the included README for further usage details, or ask a question
- The code is also available on GitHub

Download pre-trained word vectors

- Pre-trained word vectors. This data is made available under the Public Domain Dedication and License v1.0 whose full text can be found at: http://www.opendatacommons.org/licenses/pddl/1.0/.
  - Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased, 50d, 100d, 200d, & 300d vectors, 822 MB download): glove.6B.zip
  - Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors, 1.75 GB download): glove.42B.300d.zip
  - Common Crawl (840B tokens, 2.2M vocab, cased, 300d vectors, 2.03 GB download): glove.840B.300d.zip
  - Twitter (2B tweets, 27B tokens, 1.2M vocab, uncased, 25d, 50d, 100d, & 200d vectors, 1.42 GB download): glove.twitter.27B.zip
- Ruby script for preprocessing Twitter data

Citing GloVe

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation. [pdf] [bib]

Baseline Sentence to Vector

the	0.04	0.34	0.78	-0.87
cat	-0.83	-0.65	0.9	0.08
sat	0.22	-0.32	-0.19	0.11
on	0.31	-0.13	0.82	0.79
	-0.065	-0.19	0.5775	0.0275

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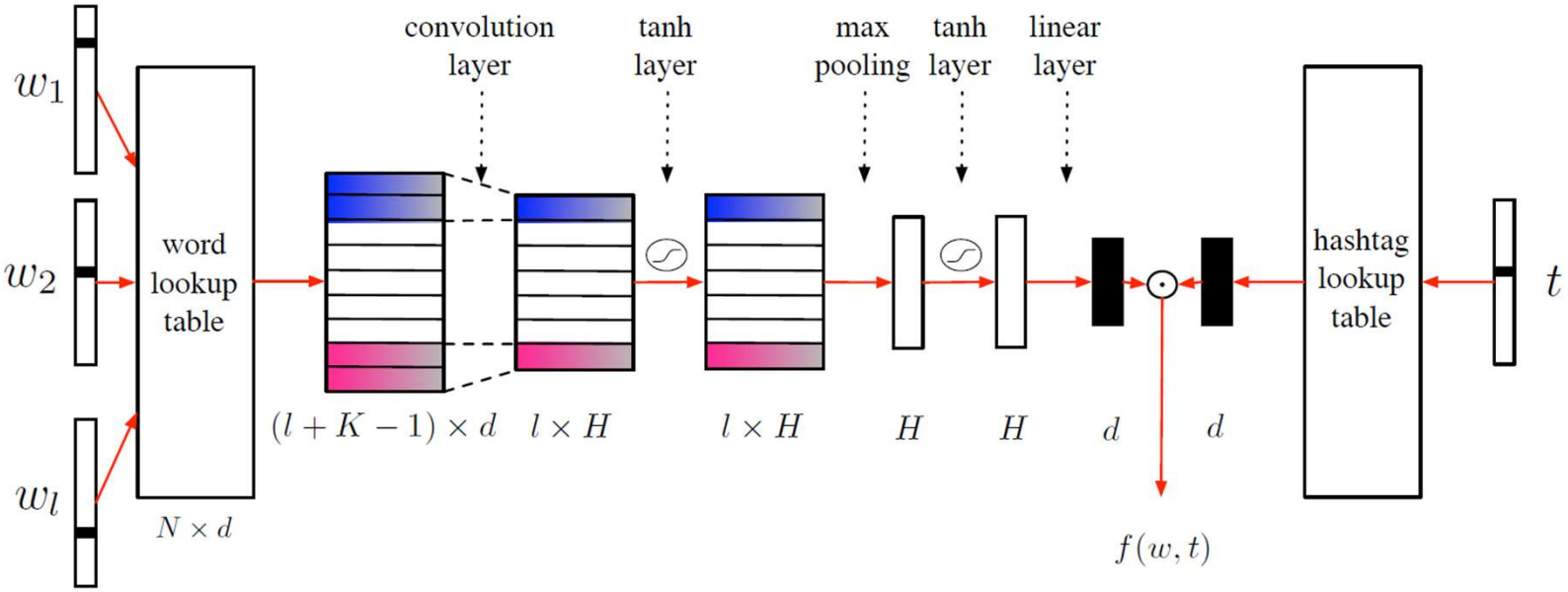
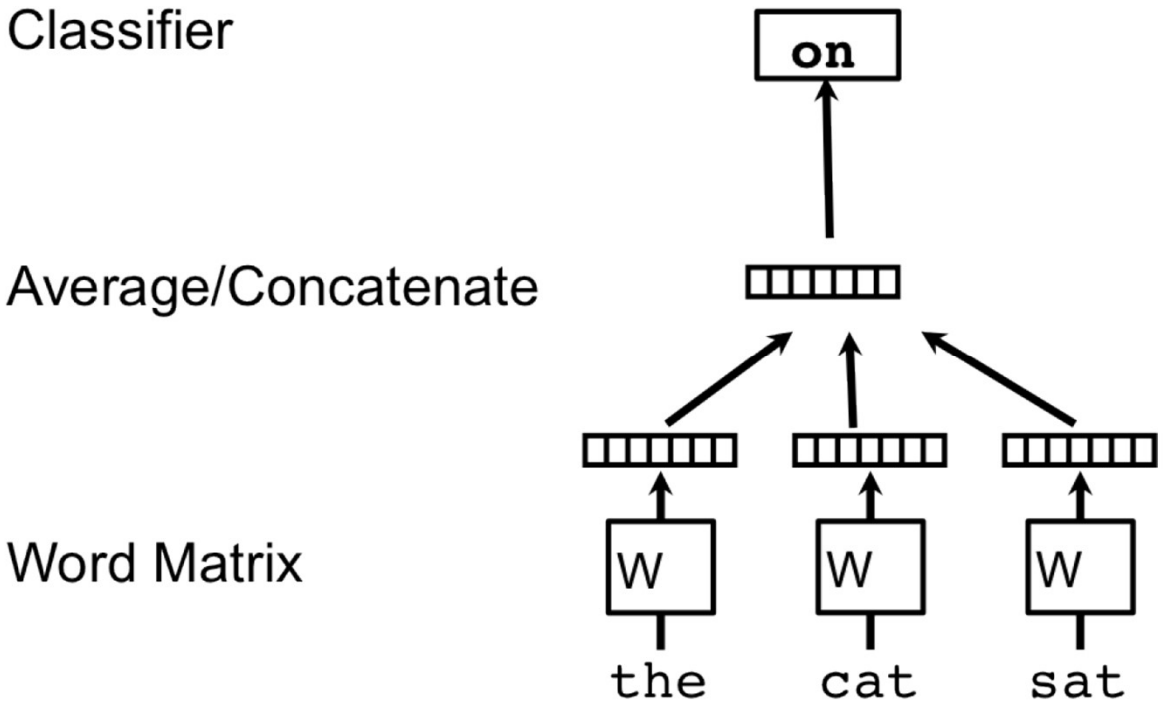
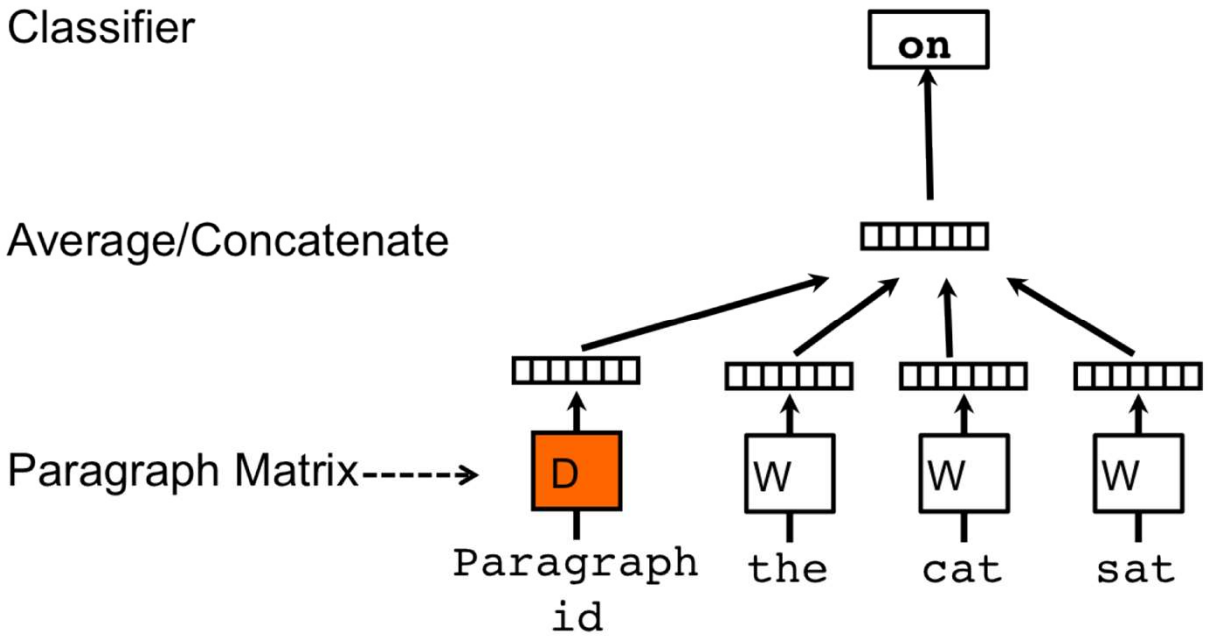


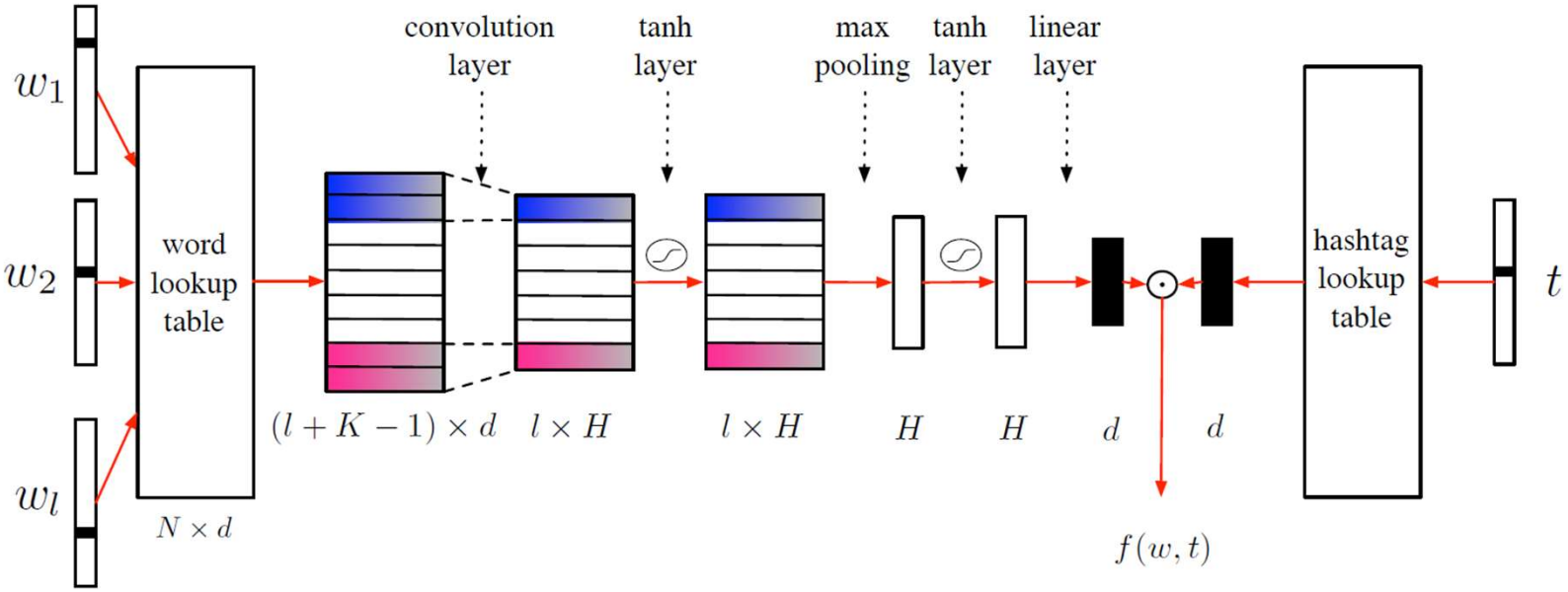
Figure 1: #TAGSPACE convolutional network $f(w, t)$ for scoring a (document, hashtag) pair.

Word Embeddings



Document Embeddings (Doc2Vec)





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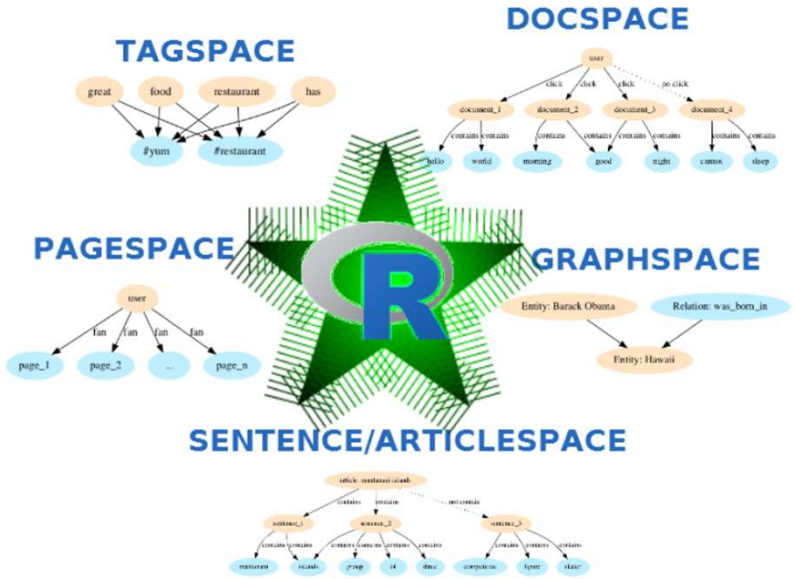
In the domain of recommendation, embedding models have had a large degree of success, starting from SVD

ruimtehol: R package to Embed All the Things! using StarSpace

This repository contains an R package which wraps the StarSpace C++ library (https://github.com/facebookresearch/StarSpace), allowing the following:

- Text classification
- Learning word, sentence or document level embeddings
- Finding sentence or document similarity
- Ranking web documents
- Content-based recommendation (e.g. recommend text/music based on the content)
- Collaborative filtering based recommendation (e.g. recommend text/music based on interest)
- Identification of entity relationships



Getting the Data Ready

```
#' Clean text for modelling
#'
#' @export
#' @description cleans text by removing apostrophe's in words, removes all
#'     punctuations and line feeds, digits and any extraneous spaces
#' @param x a character vector
#' @return cleaned character vector
cleanText <- function(x){
    output <- x %>%
        ## remove "'" from words to change "didn't" to "didnt"
        stringr::str_replace_all(., "'", "") %>%
        ## remove punctuation, double quotes and line feeds
        stringr::str_replace_all(., "[\\p{P}\\p{S}\r\n\t]", " ") %>%
        ## remove strings of numbers
        stringr::str_replace_all(., "[0-9]+", " ") %>%
        ## seperate by only one space
        stringr::str_replace_all(., "[ ]{2,}", " ") %>%
        ## remove any whitespace at beginning or end of line
        stringr::str_trim(.) %>%
        ## lower case everything
        tolower(.)

    return(output)
}
```

Getting the Data Ready

```
288  287,forkilt,forklift
289  288,forklifted,forklifted
290  289,forkklift,forklift
291  290,forklfit,forklift
292  291,forklft,forklift
293  292,forklifter,forklift
294  293,forklfting,forklifting
295  294,forklif,forklift
296  295,forklife,forklift
297  296,forkliftiting,forklifting
298  297,forkliftt,forklift
299  298,forkligt,forklift
300  299,forkligting,forklifting
301  300,forkliift,forklift
302  301,forklilft,forklift
303  302,forklioft,forklift
304  303,forklirt,forklift
305  304,forklist,forklift
306  305,forklit,forklift
307  306,forkllift,forklift
308  307,forkllioft,forklift
309  308,forksjust,forks just
310  309,forksthey,forks they
311  310,forksw,forks
312  311,forktine,fork tine
```

Running the Algorithm

```
# set seed for tagspace
set.seed(321)
model <- ruimtehol::embed_tagspace(x = trainList$x,
                                   y = trainList$y,
                                   dim = 30,
                                   early_stopping = 0.8,
                                   validationPatience = 10,
                                   epoch = 100,
                                   lr = 0.01,
                                   loss = "hinge",
                                   negSearchLimit = 10,
                                   adagrad = FALSE,
                                   initRandSd = 0.01,
                                   ngrams = 1,
                                   minCount = 20,
                                   thread = 6)
```

Evaluating TagSpace

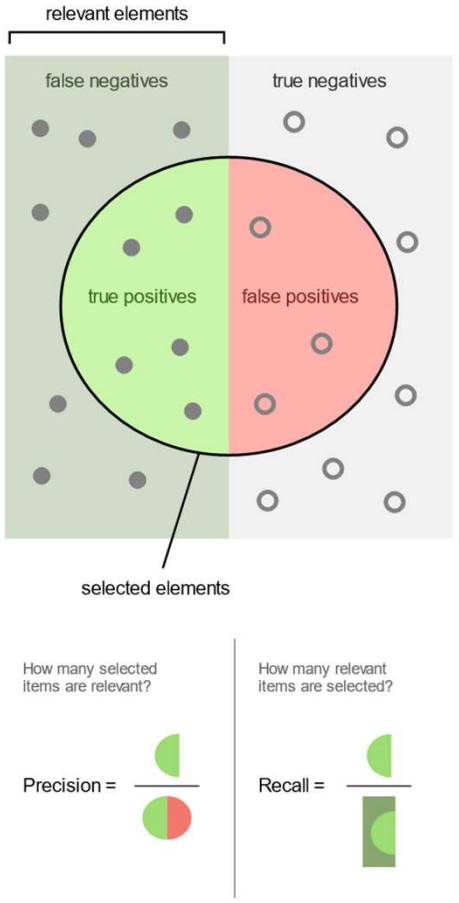
Precision at 1

Recall at 10

Mean Rank of True Labels

1 #Bunnings
2 #summer
3 #garagestorage
4 #shed

bunnings Start the new year organised with our versatile garage storage solutions ✅ @pinnaclehardware's compact workbench will help declutter even the smaller working spaces. Tap to view product details. #bunnings #garagestorage



Where we are.

TagSpace model to convert incident descriptions to embeddings

Where we want to be.

Descriptive analytics.

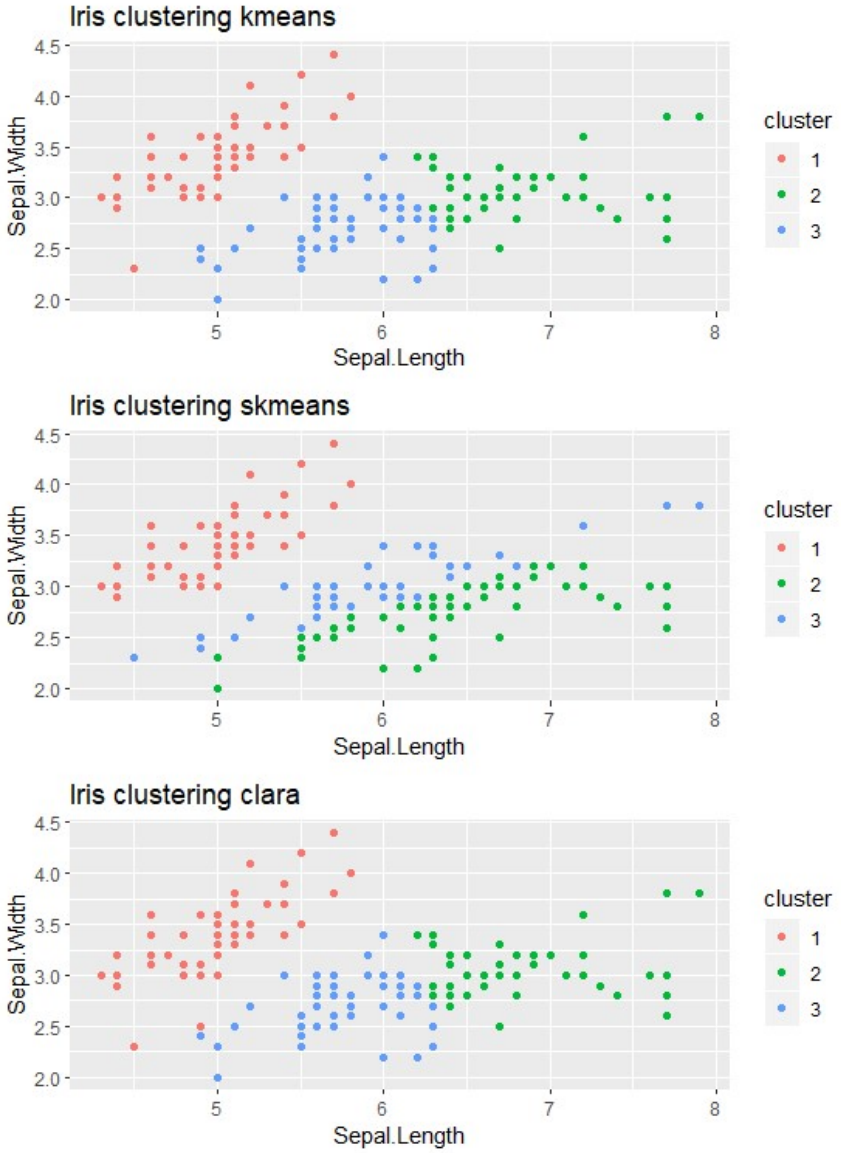
- Do the incidents fall into broad categories?
- What are the characteristics of those categories?

What is Clustering?

kmeans – partition the points into *k* groups such that the sum of squares from points to the assigned cluster centres is minimized

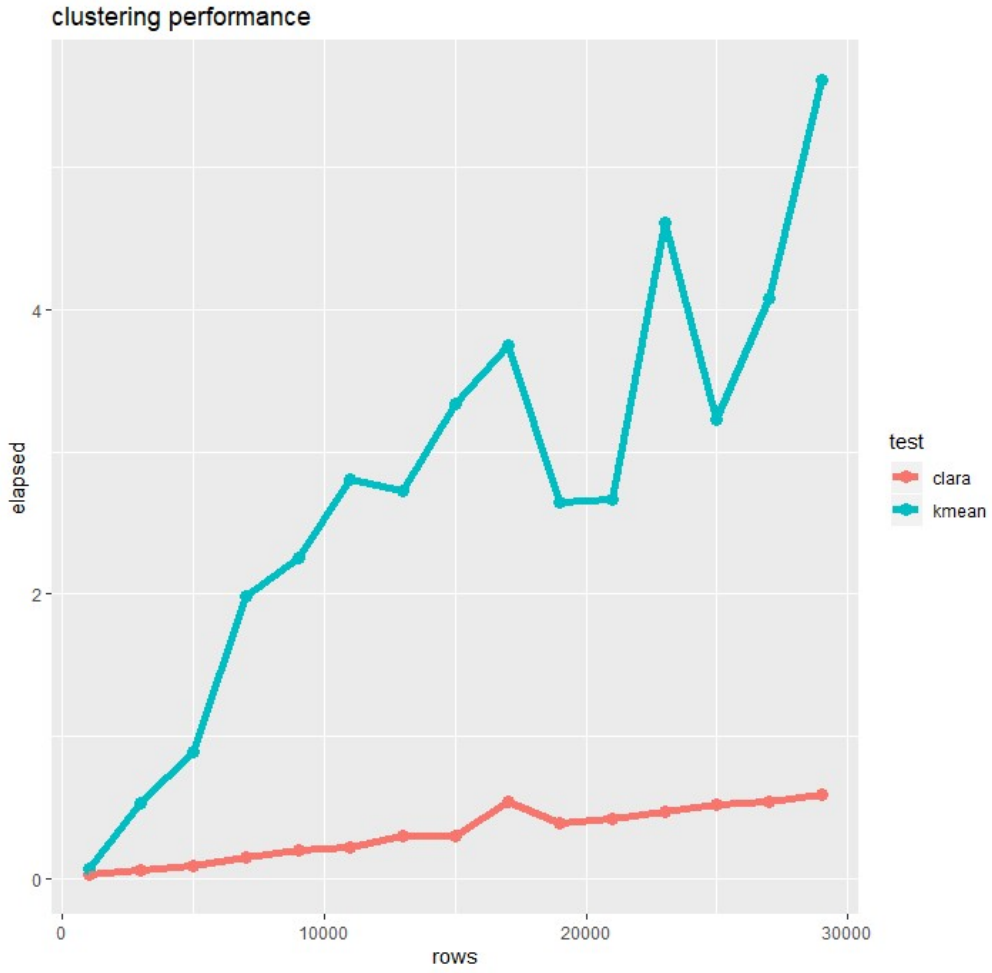
skmeans (spherical kmeans) – similar to kmeans but uses cosine similarity distance instead.

clara (Clustering Large Applications) – similar to kmeans but takes samples of the data to be more resource efficient.



What is Clustering?

kmeans vs clara –
clara is significantly less computational expensive compared to kmeans.



Clustering

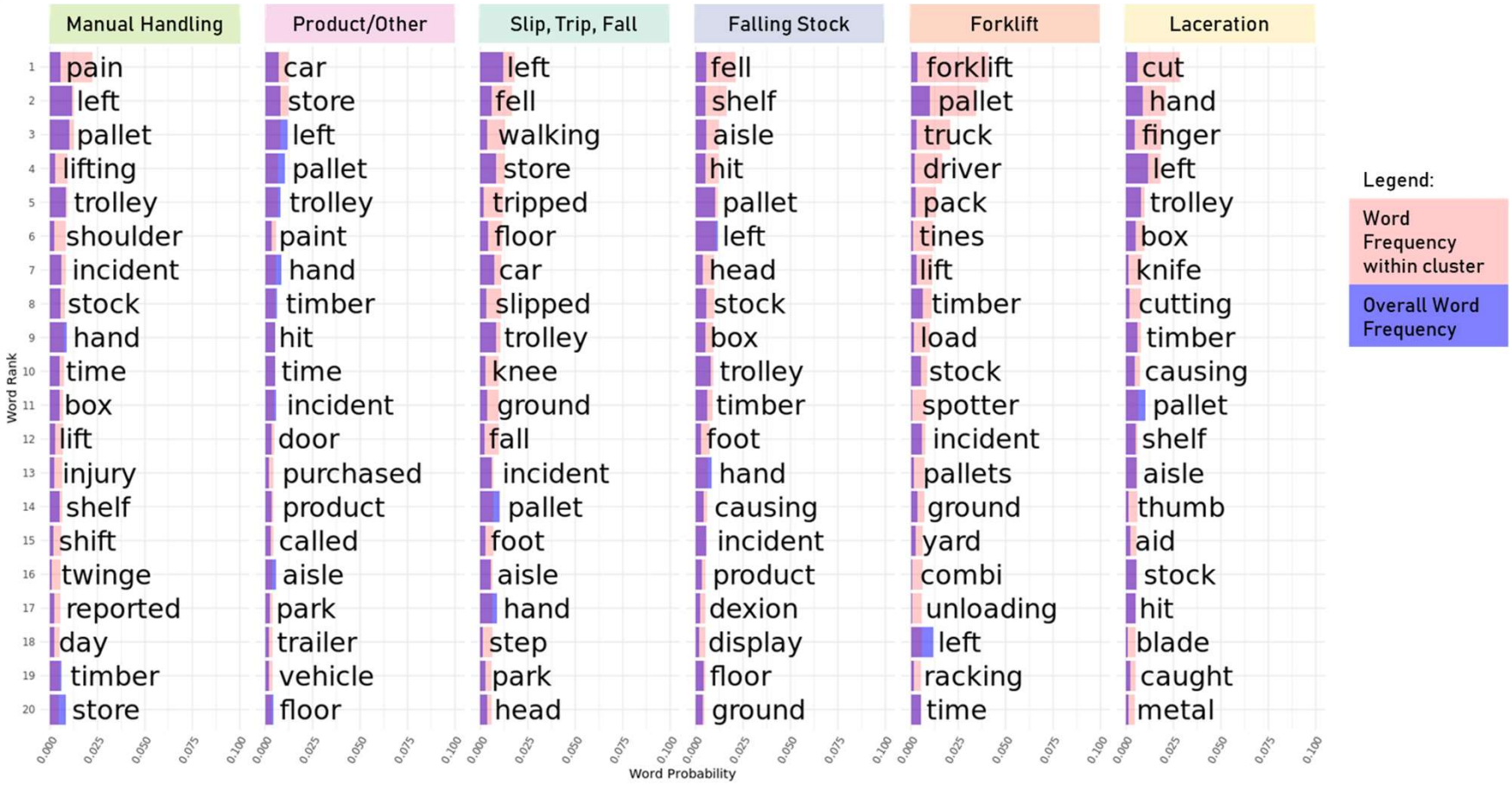
```
## get the functions for clustering options
cluster_list <- list(

    kmeans = stats::kmeans(
        x = dt,
        centers = 7,
        iter.max = 50),

    clara = cluster::clara(
        x = dt,
        k = 7,
        samples = 100),

    skmeans = skmeans::skmeans(
        x = dt,
        k = 7)
)
```

Cluster Evaluations (Quantitative)

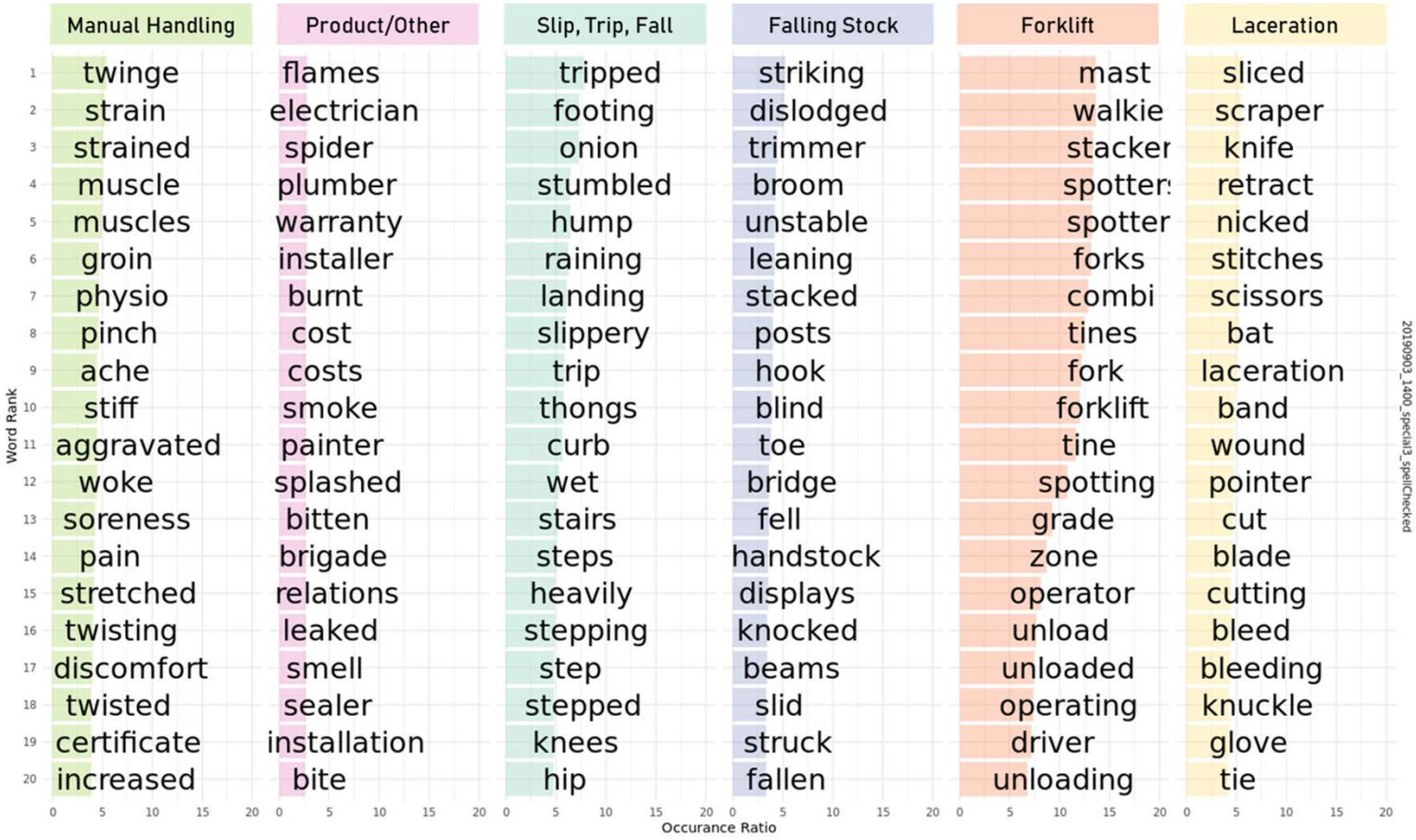
Silhouette – a measurement of how close a point is to every other point in the same cluster compared to every point in the next closest cluster.

Dispersion – a measurement of how compact the points in a cluster are.

Cluster Evaluations (Qualitative)



Cluster Evaluations (Qualitative)



Where are we.

Descriptive analytics.

What next?

Predictive and Prescriptive Analytics

- Can we predict safety incidents?
- Can we prevent incidents from occurring or minimise their impact?


WATCH OUT FOR
FORKLIFTS