Word embeddings for predicting judgment: An application to risk perception

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Studying Judgments

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In order to study peoples' judgments we need to

- Uncover the mental representation
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Psychometric Approach

1. Ask participants to make the judgment

How risky is X?

2. Ask participants to rate the object or concept on some additional variables

How controllable is X? How fatal is X?

3. Use techniques like linear regression to learn the relationship between these variables and the judgment

riskiness ~ controllability + fatality + …

Slovic. P. (1987). Perception of Risk. *Science.*

Challenges

Psychometric approach has numerous limitations:

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- Impoverished representations
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Can we use text analysis to study judgments?

- Uncover the mental representation → word embeddings
- Learn the mapping → (off the shelf) machine learning

Word Embeddings

Objects and concepts are represented in terms of vectors in a very high dimensional semantic space

Vectors trained on co-occurrence statistics in large-scale natural language data

Capture knowledge/meaning with similar concepts closer together in this space

Mikolov et al. (2013)

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I will use pretrained Word2Vec vectors

- Representations for over 3 million words and phrases
- Each vector has 300 dimensions
- Trained on 100 billion word Google News corpus

Mikolov et al. (2013)

Risk Rating Task

Participants were asked to rate the riskiness of different risks on a scale of -100 (very safe) to +100 (very risky)

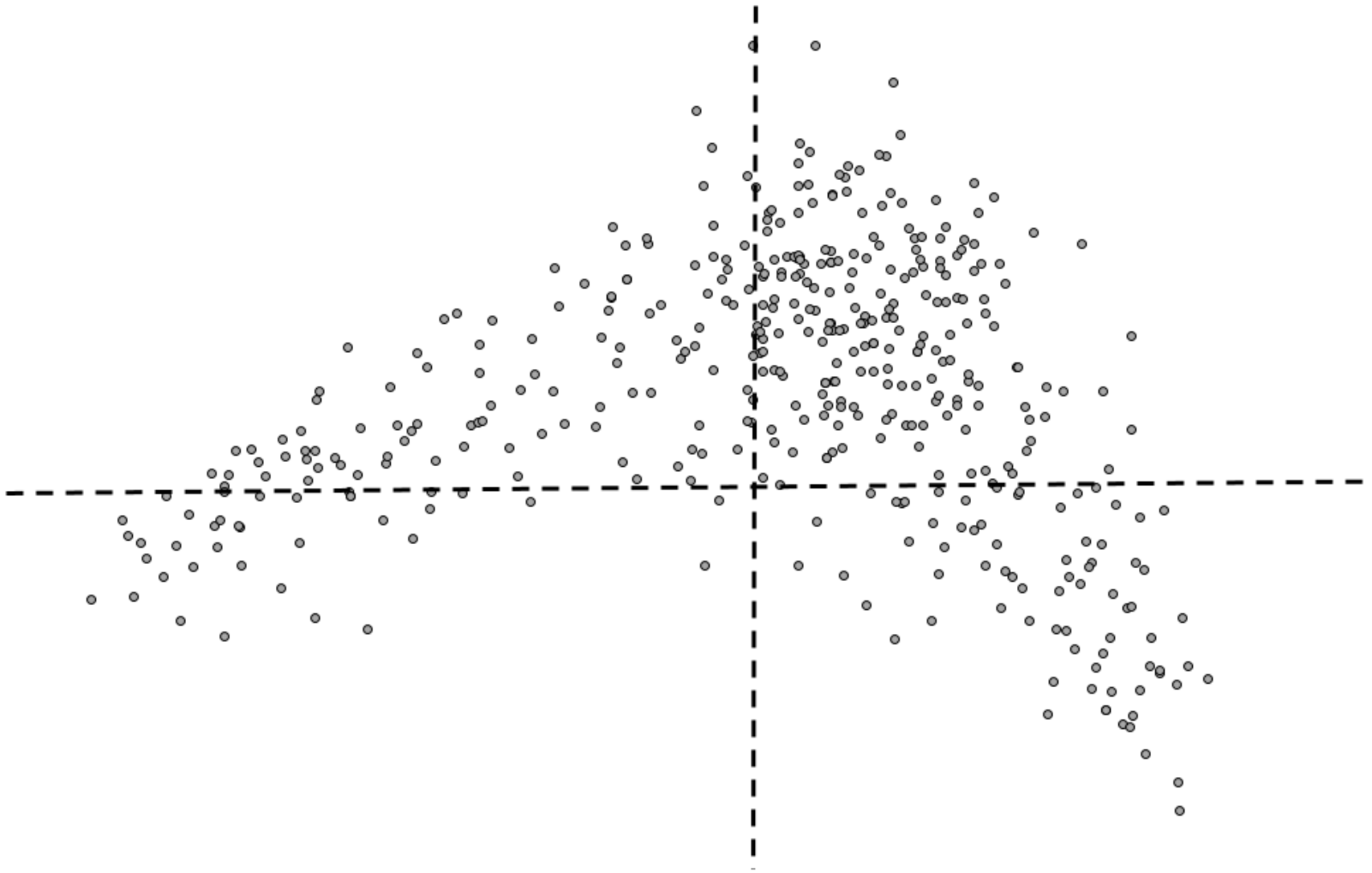
Study 1A: 75 participants and 125 technological risks

Study 1B: 75 participants and 125 activity-based risks

(based on Slovic, 1987)

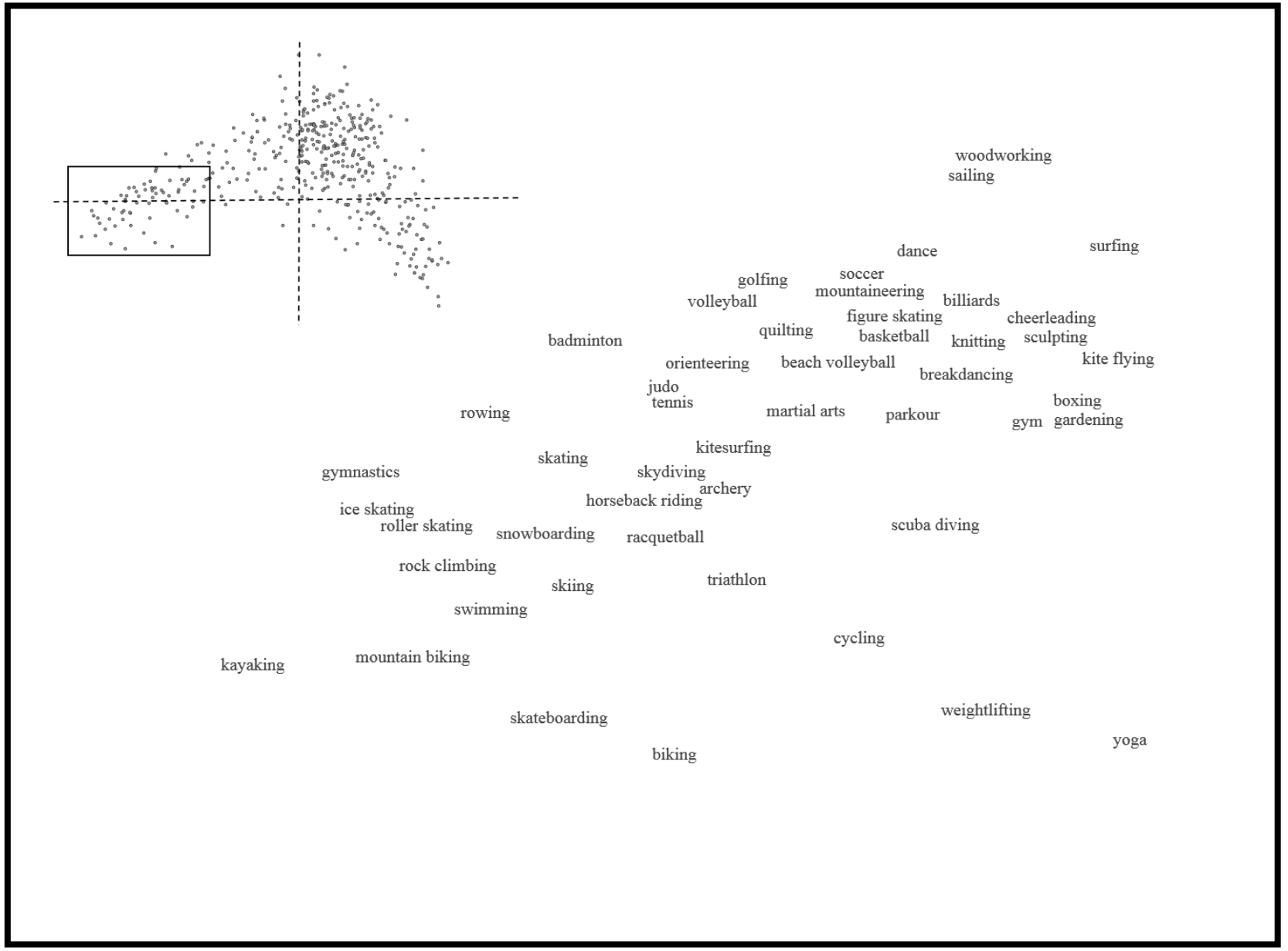
Study 2: 300 participants and 200 general risks

(generated by separate set of participants)



Approx. 450 risks

2D projection of 300D Word2Vec space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badminton
orienteering
beach volleyball
kite flying
breakdancing
judo
tennis
boxing
rowing
martial arts
parkour
gym
gardening
kitesurfing
skating
gymnastics
skydiving
archery
horseback riding
ice skating
roller skating
snowboarding
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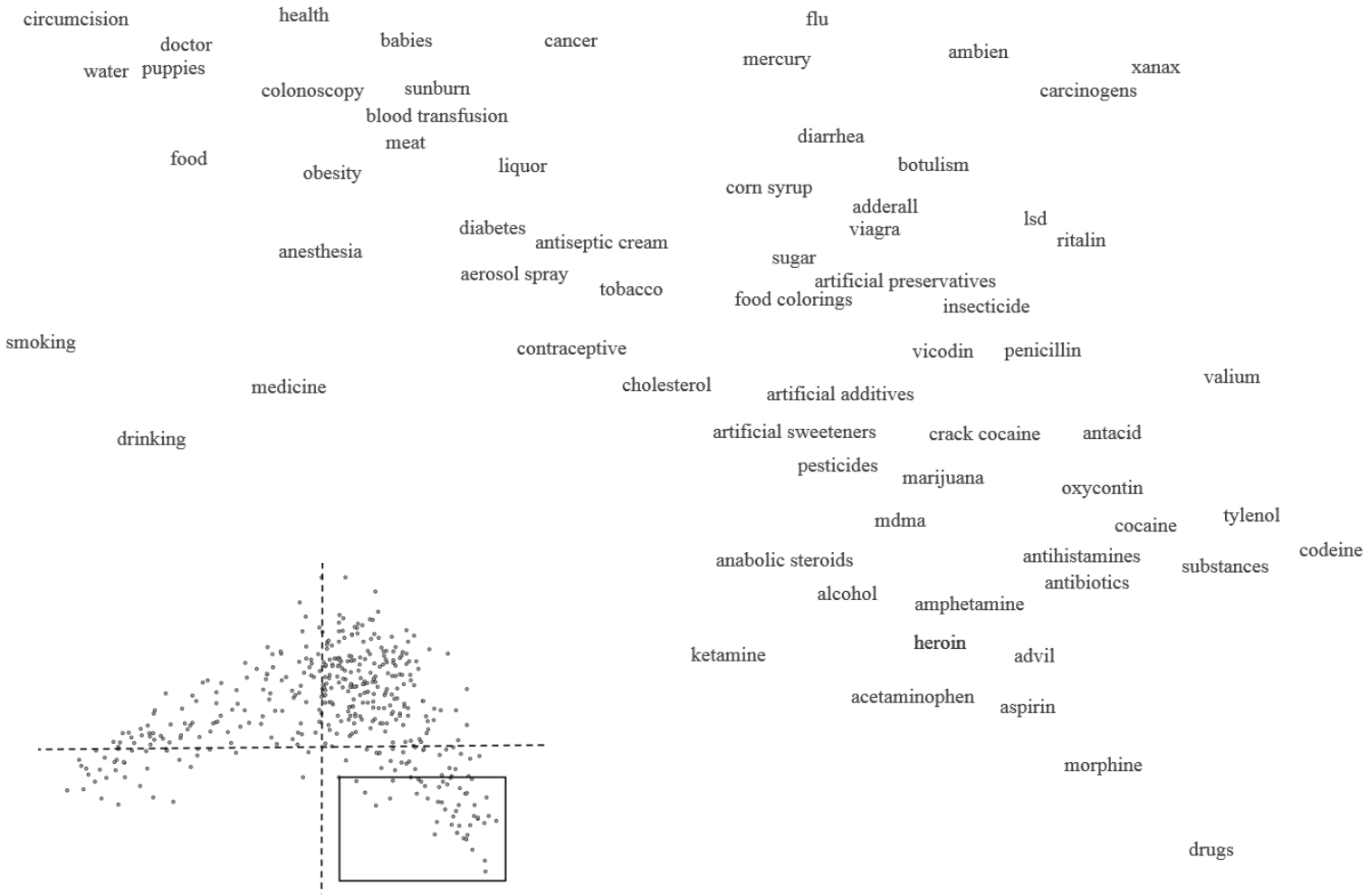
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food
obesity
liquor
botulism
corn syrup
adderall
lsd
diabetes
viagra
antiseptic cream
ritalin
anesthesia
sugar
aerosol spray
artificial preservatives
tobacco
food colorings
insecticide
smoking
contraceptive
vicodin
penicillin
valium
medicine
cholesterol
artificial additives
drinking
artificial sweeteners
crack cocaine
antacid
pesticides
marijuana
oxycontin
mdma
cocaine
tylenol
codeine
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alcohol
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heroin
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Predicting Risk Ratings

Risk Source	300-d Word Vector	Risk Rating	
bicycle	[0.81, 0.43, ... 0.30]	12	Training
airplane	[0.24, 0.12, ... 0.29]	64	
train	[0.11, 0.05, ... 0.85]	-22	
.	.	.	
.	.	.	
.	.	.	
go-cart	[0.52, 0.76, … 0.01]	??	Test
seaplane	[0.98, 0.17, ... 0.08]	??	

Mappings learnt with support vector regressions

Psychometric Rating Task

A separate group of participants was asked to evaluate the risk sources on 9 dimensions taken from Slovic (1987)

Study 1A: 75 participants and 125 technological risks

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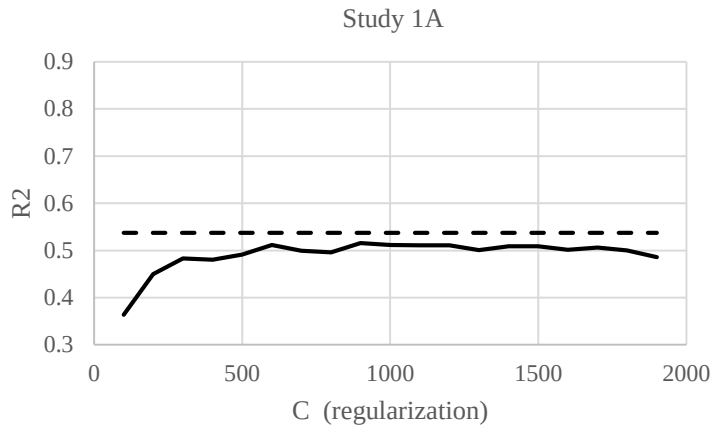
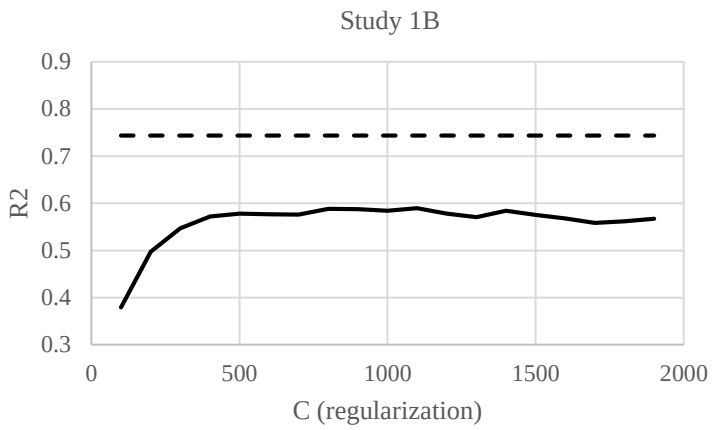
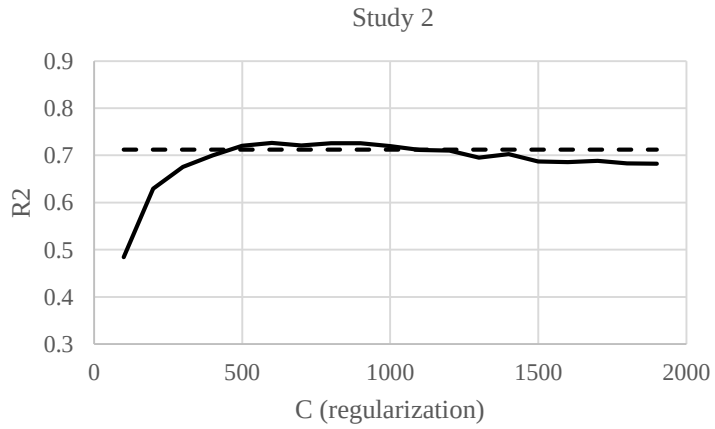
Study 2: 300 participants and 200 general risks

These ratings were use to test the word embeddings approach against the (standard) psychometric approach

Predicting Risk Ratings



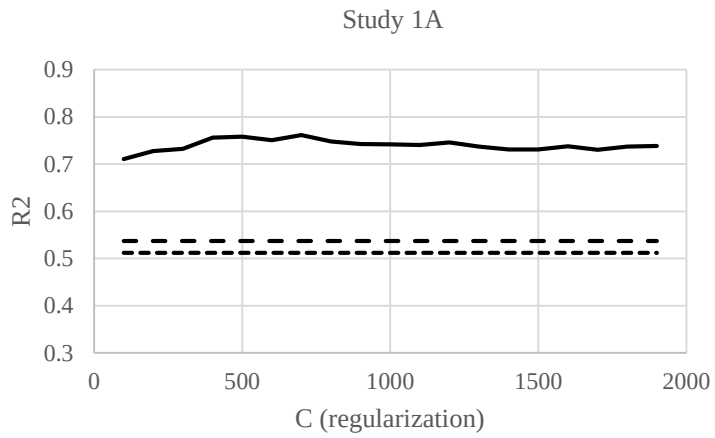


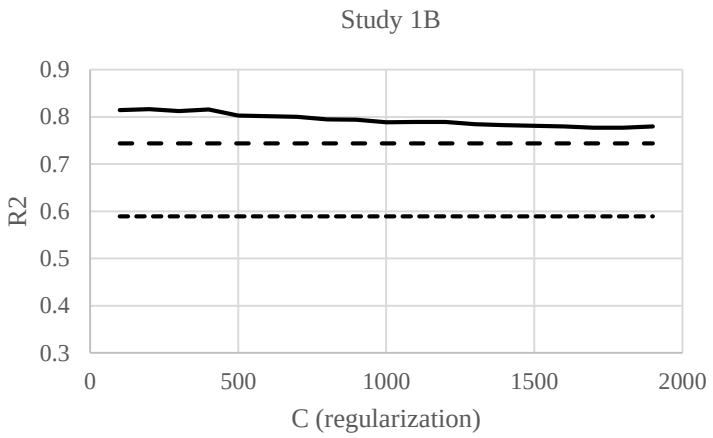


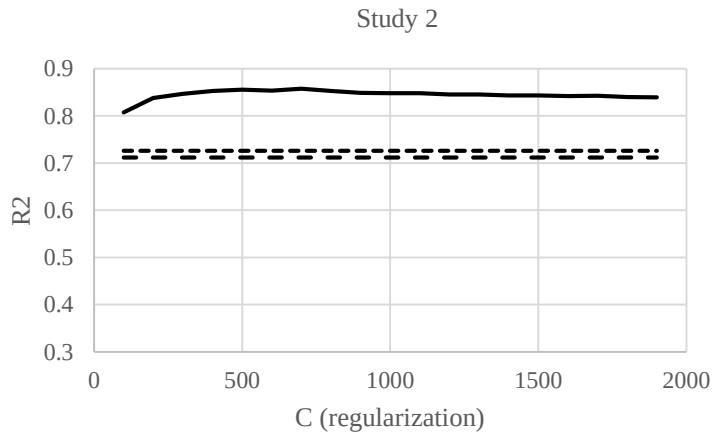
Word embeddings
Psychometric

C is SVR regularization parameter
Predictions evaluated on 10% hold-out data

Predicting Risk Ratings







Combined
Psychometric
Word embeddings (best C)

C is SVR regularization parameter
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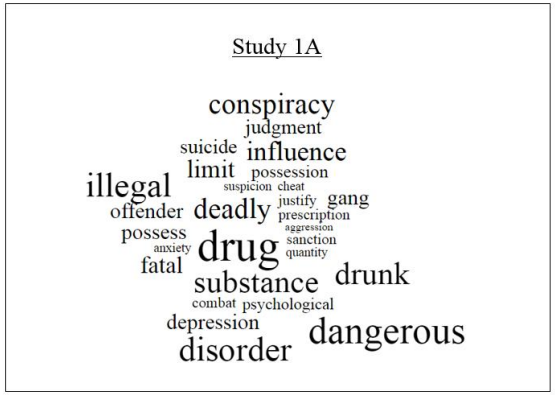
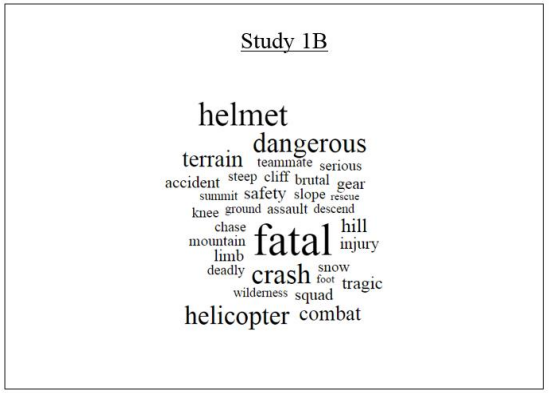
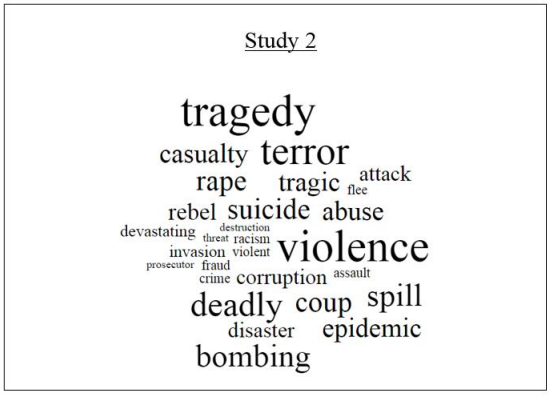
Risk Associations

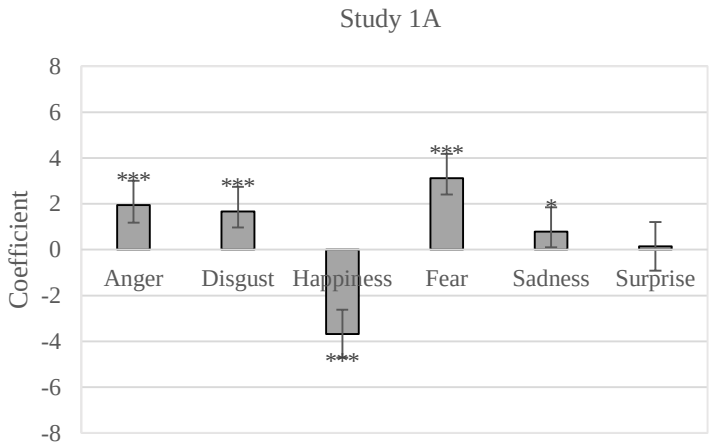


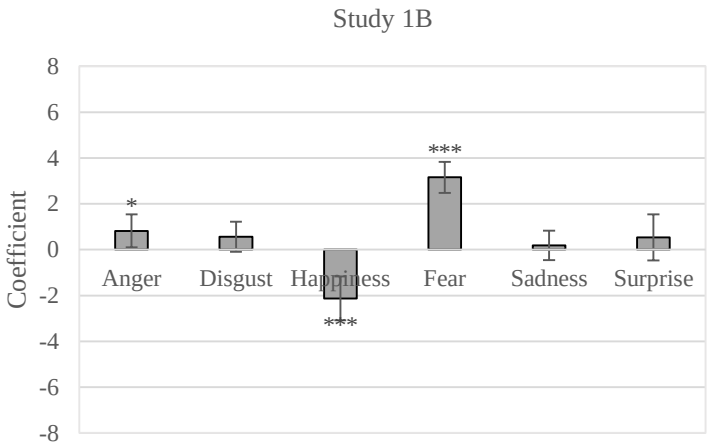


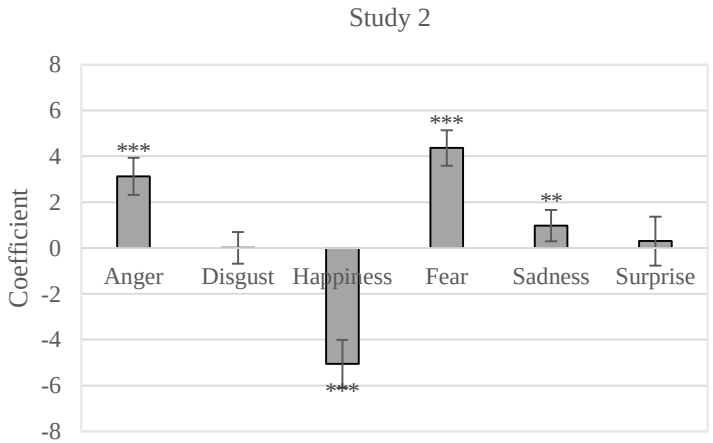


Words with the highest proximity to high-risk (relative to low-risk) risk sources in Word2Vec embeddings space

Emotions & Risk Associations







Errors bars are 95% confidence intervals

*** p < 0.001
** p < 0.01
* p < 0.05

Emotions evaluated using Mohammed & Turney (2013) emotion dictionaries

Psychometric Mappings

Do risk associates map on to the 9 psychometric dimensions?

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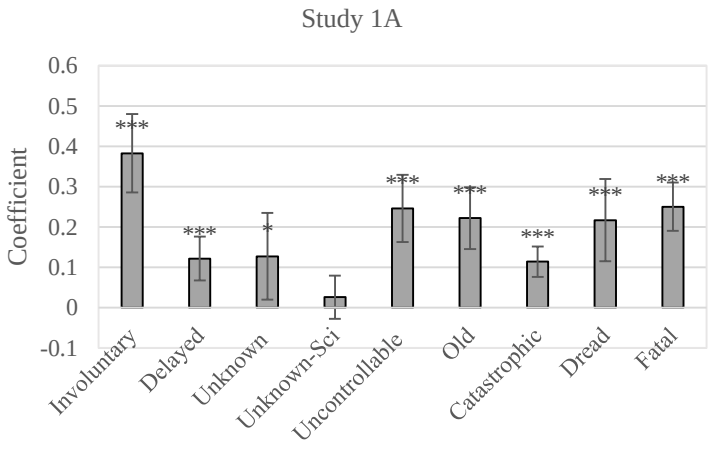
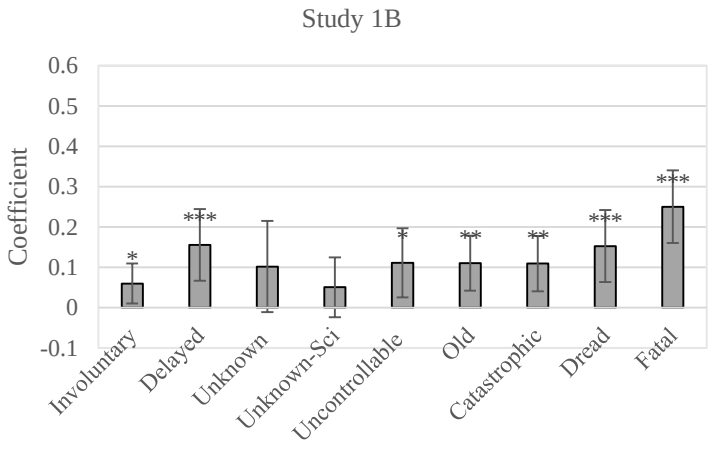
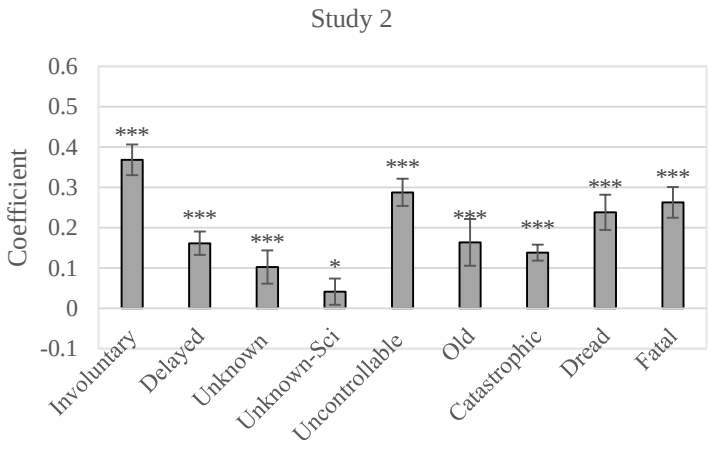
To test this I asked a separate group of participants to write down words that come to their mind when they think of risk sources that are voluntary, involuntary, delayed, immediate etc.

I then calculated the risk associations of these word lists

Psychometric Mappings







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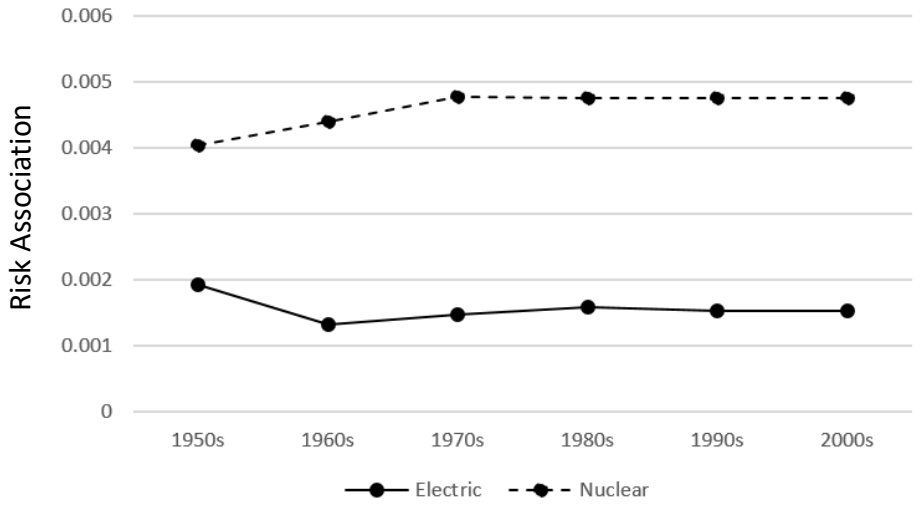
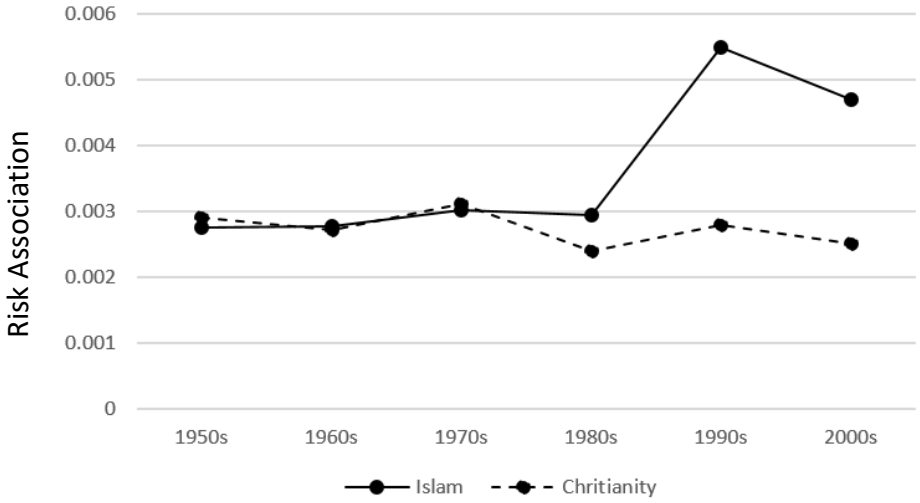
Word embeddings approach can be applied to most naturalistic judgment tasks!





Risk associations of various concepts over time, based on Word2Vec models trained on historical language data