

Multimodal Analysis and Prediction of Latent User Dimensions

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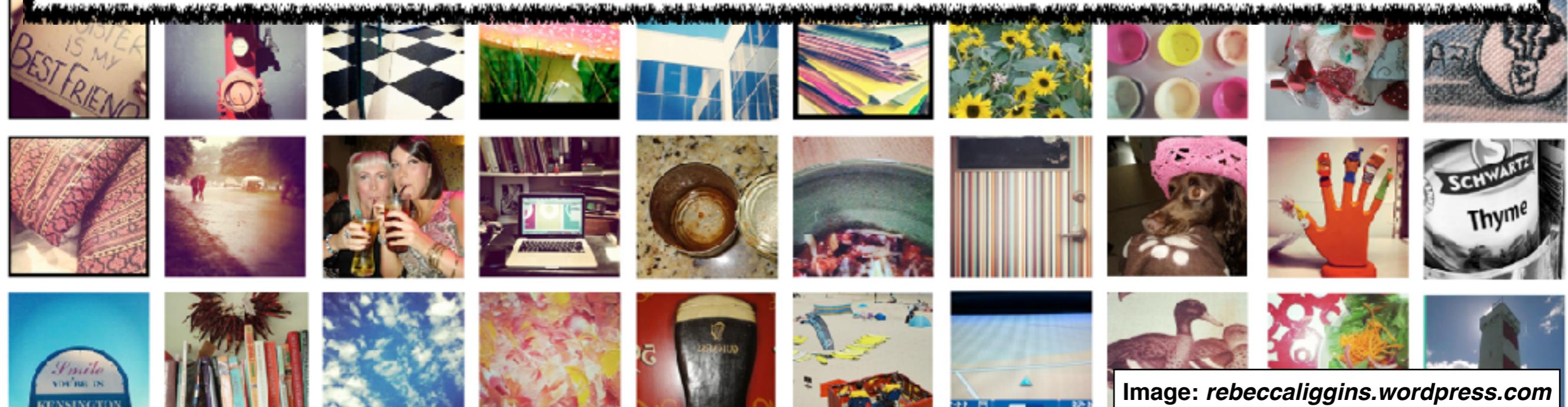
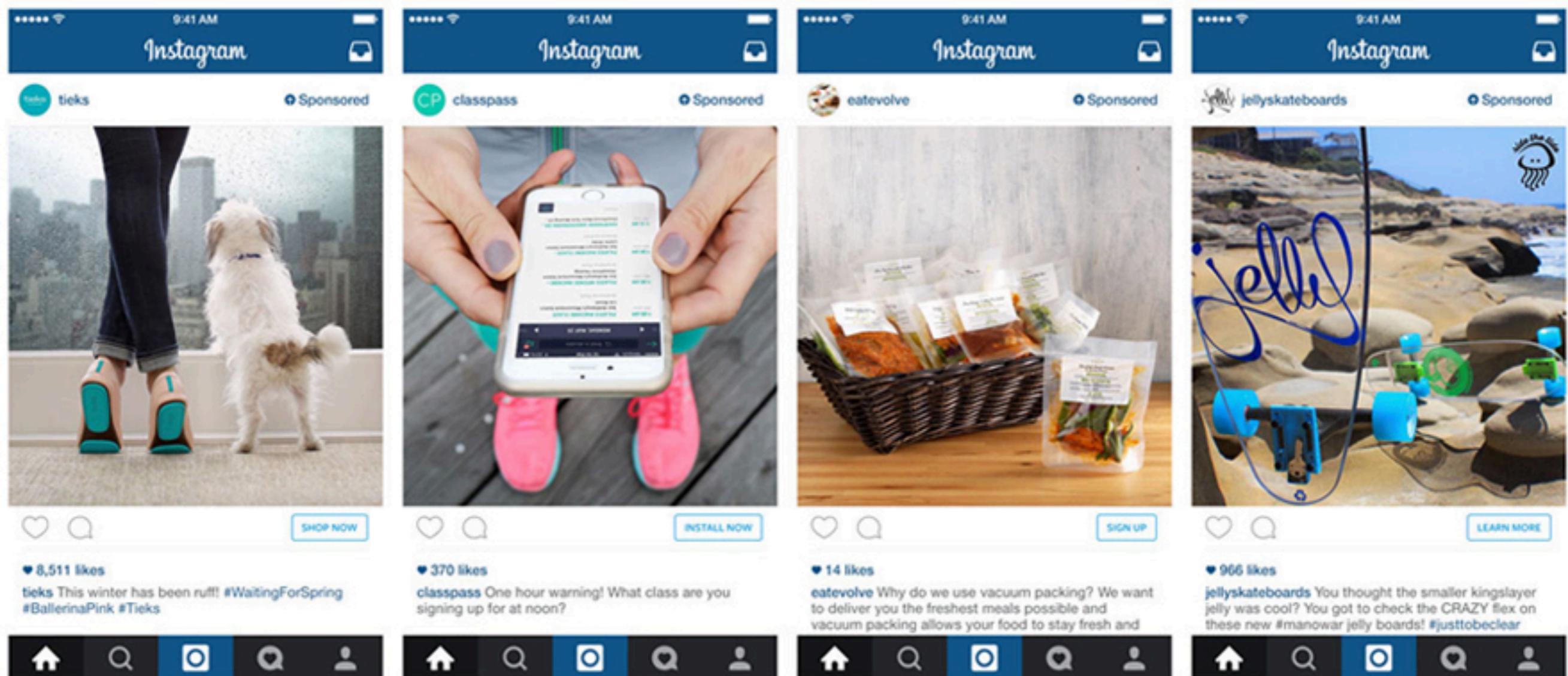


Image: rebeccaliggins.wordpress.com

1.8 *Billion* Images / Day!



Conclusions

1. Correlational techniques provide interpretable psychological insight into personality and gender.
2. For the task of personality prediction, multimodal models outperform both visual features and textual features in isolation, using a relatively small dataset.

Outline

1. Dataset
2. Features
3. Correlational Analysis
4. Multimodal Prediction

Dataset

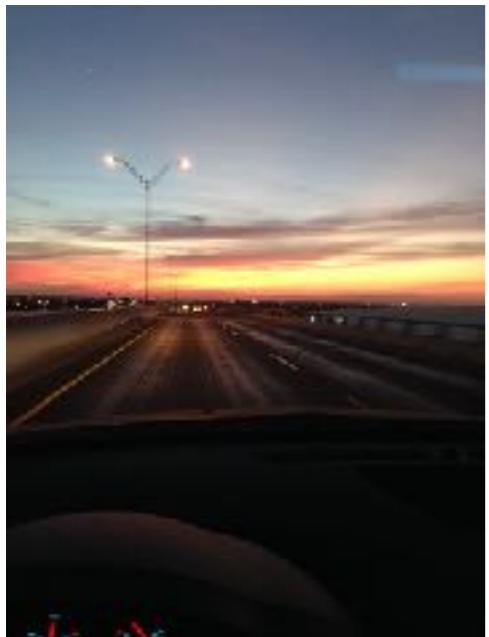
- Sam Gosling & James Pennebaker, UT Austin
- Fall 2015 introductory undergraduate psych class
- Students from all majors
- Images, captions, gender, & personality
- 1,353 students



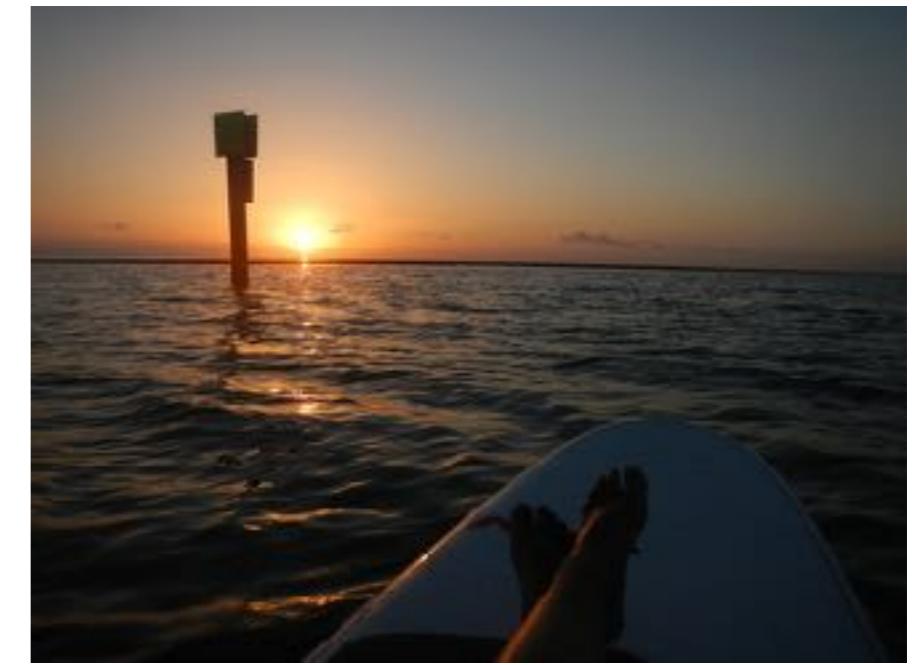
The real me is right behind you.



Gotta find something to do when I have nothing to say.

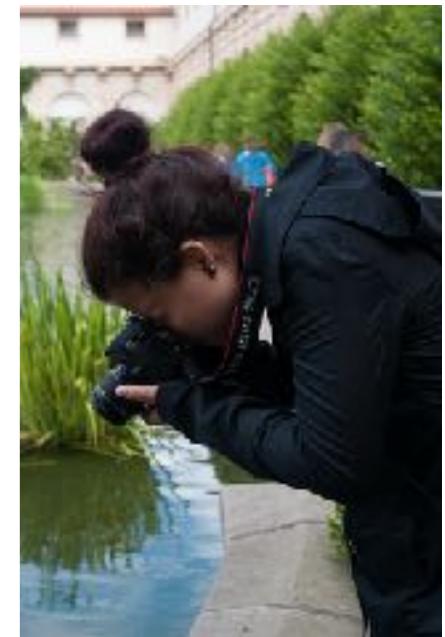


I crossed this bridge almost every day for 18 years and never got tired of it.



I'd rather be on the water.

The littlest things are always so pretty (and harder to capture).



Big 5 Personality Traits

Openness

Artistic

Curious

Original

Conscientiousness

Efficient

Organized

Thorough

Extraversion

Assertive

Enthusiastic

Outgoing

Agreeableness

Appreciative

Sympathetic

Trusting

Neuroticism

Anxious

Unstable

Worrying

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Feature Extraction

- Want meaningful and interpretable features with some connection to the user

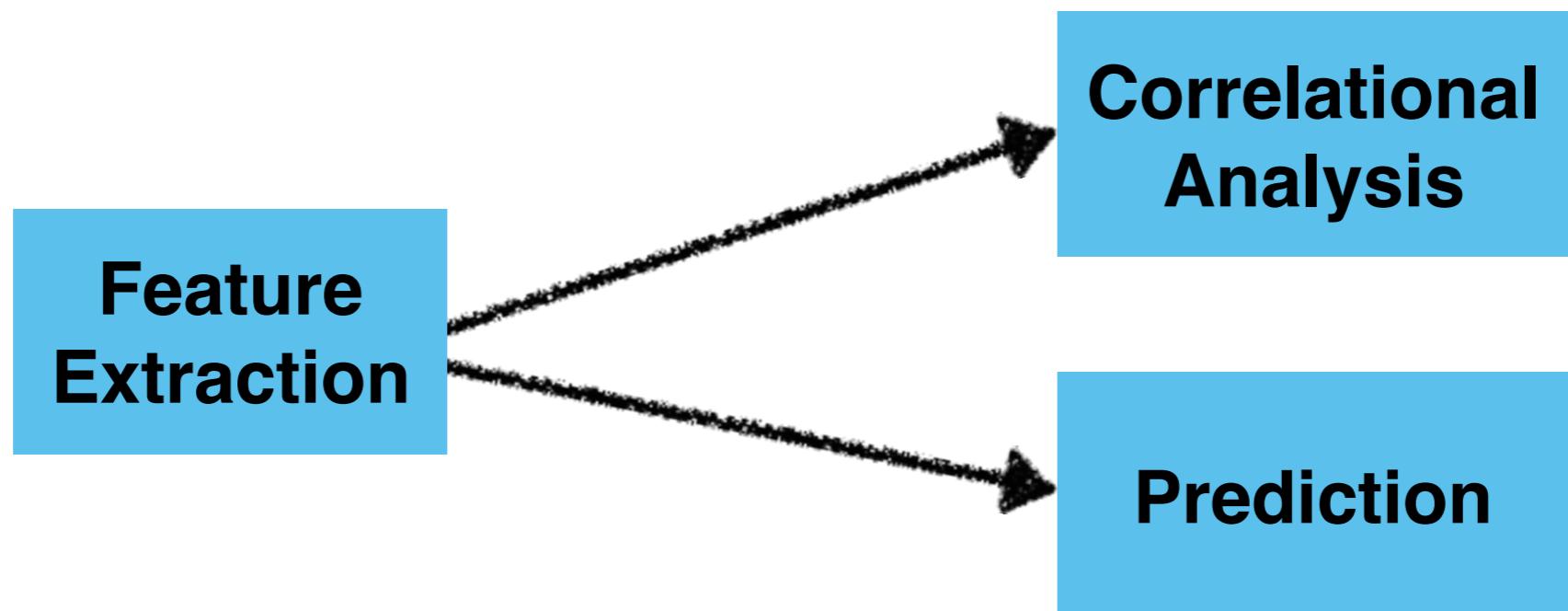
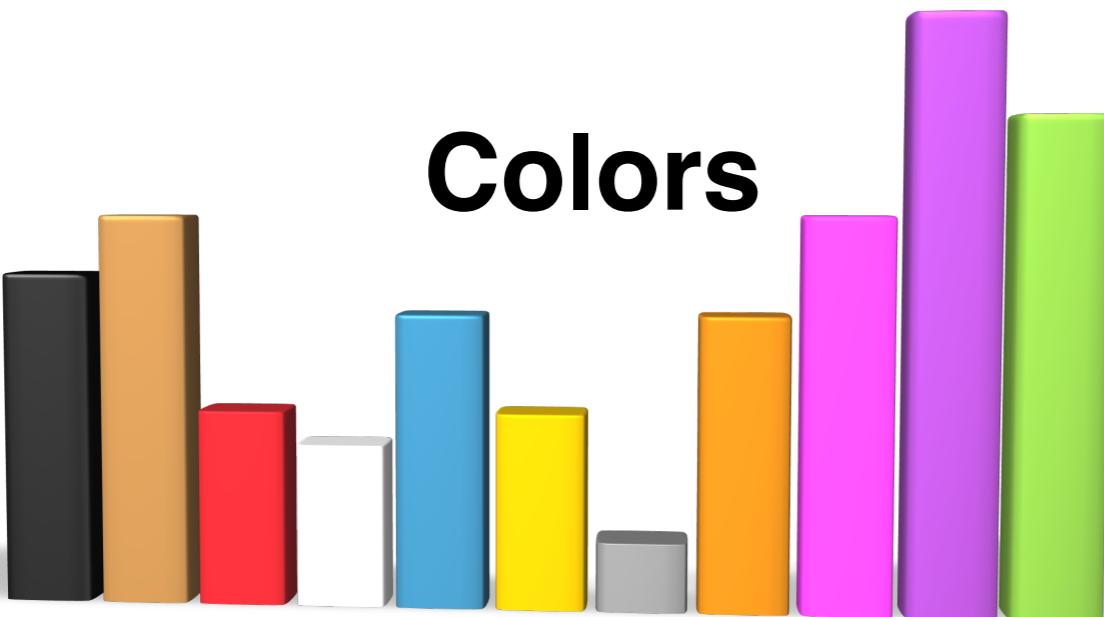


Image Attributes



Faces



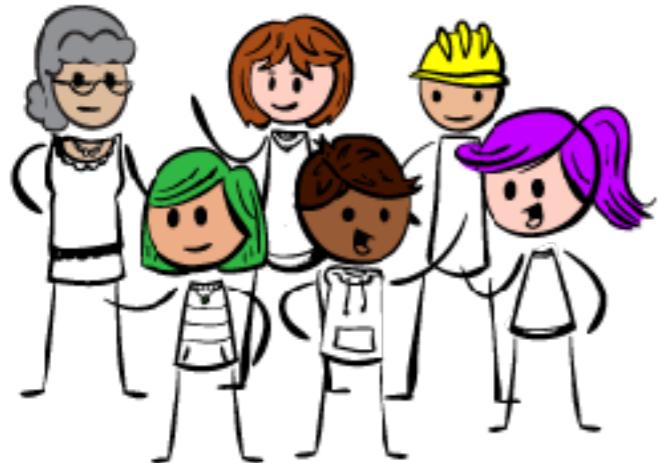
Scenes



Objects



Caption Attributes



Named Entities



Readability



word2vec

LIWC

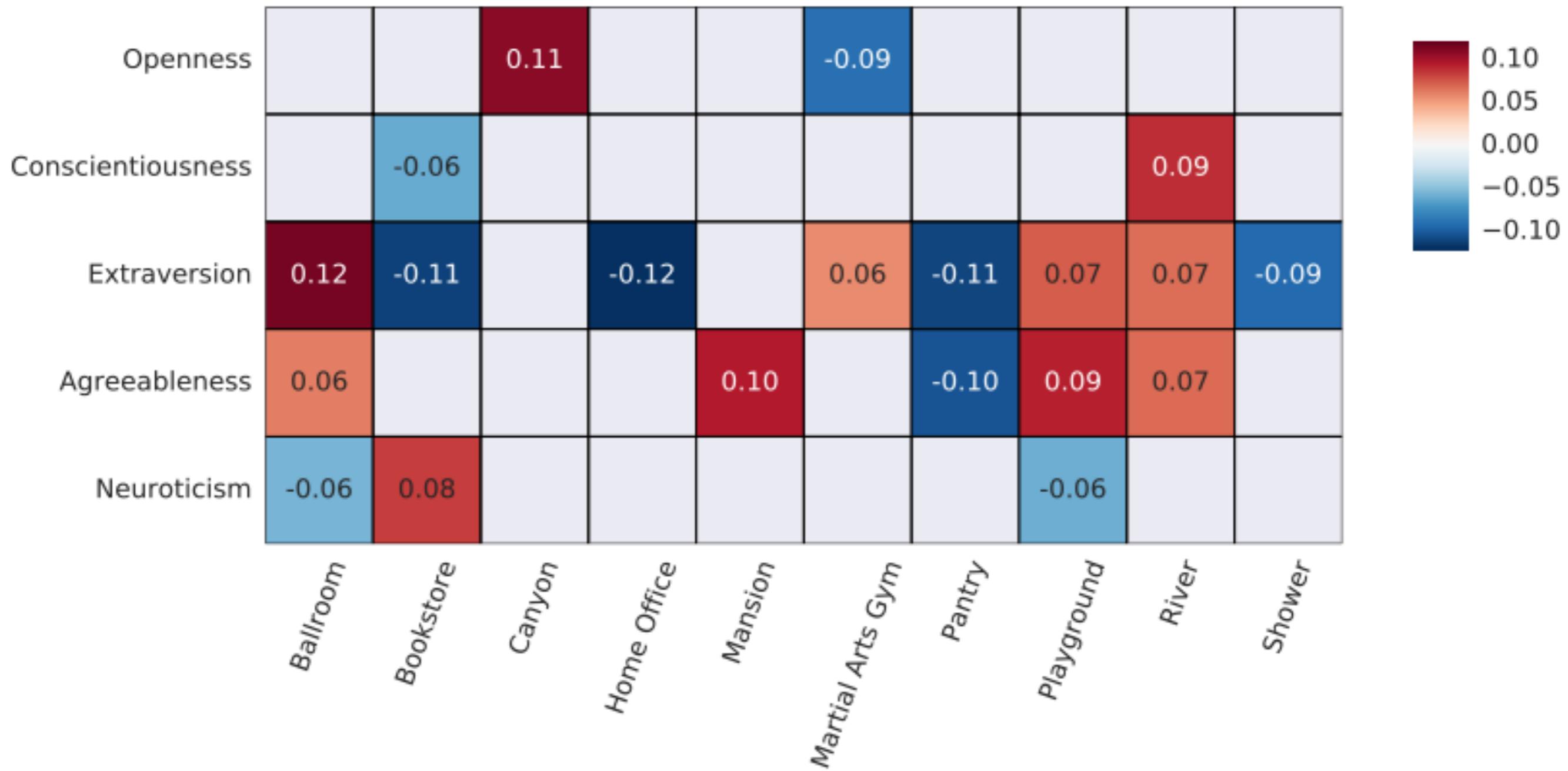
Anxiety
worried
fearful
nervous

Causation
because
effect
hence

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Selected Correlations: Scenes



Selected Gender Effects: Scenes

<u>Female</u>	<i>Effect Size</i>	<u>Male</u>	<i>Effect Size</i>
Beauty Salon	0.347	Office	0.290
Ice Cream Parlor	0.340	Football Stadium	0.267
Slum	0.286	Baseball Stadium	0.222
Herb Garden	0.224	Gas Station	0.222
Art Studio	0.221	Music Studio	0.222



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Classification Task

- **Data division:**
High segment $> \mu + 0.5\sigma$
Low segment $< \mu - 0.5\sigma$
- **Random forest:** 500 trees
(10-fold cross validation across individuals)
- **Baseline:** Most common training class
- **Comparison:** Mairesse et al. 2007

Image-Enhanced Unigrams (IEUs)

Color: yellow, orange

Scene: kitchen

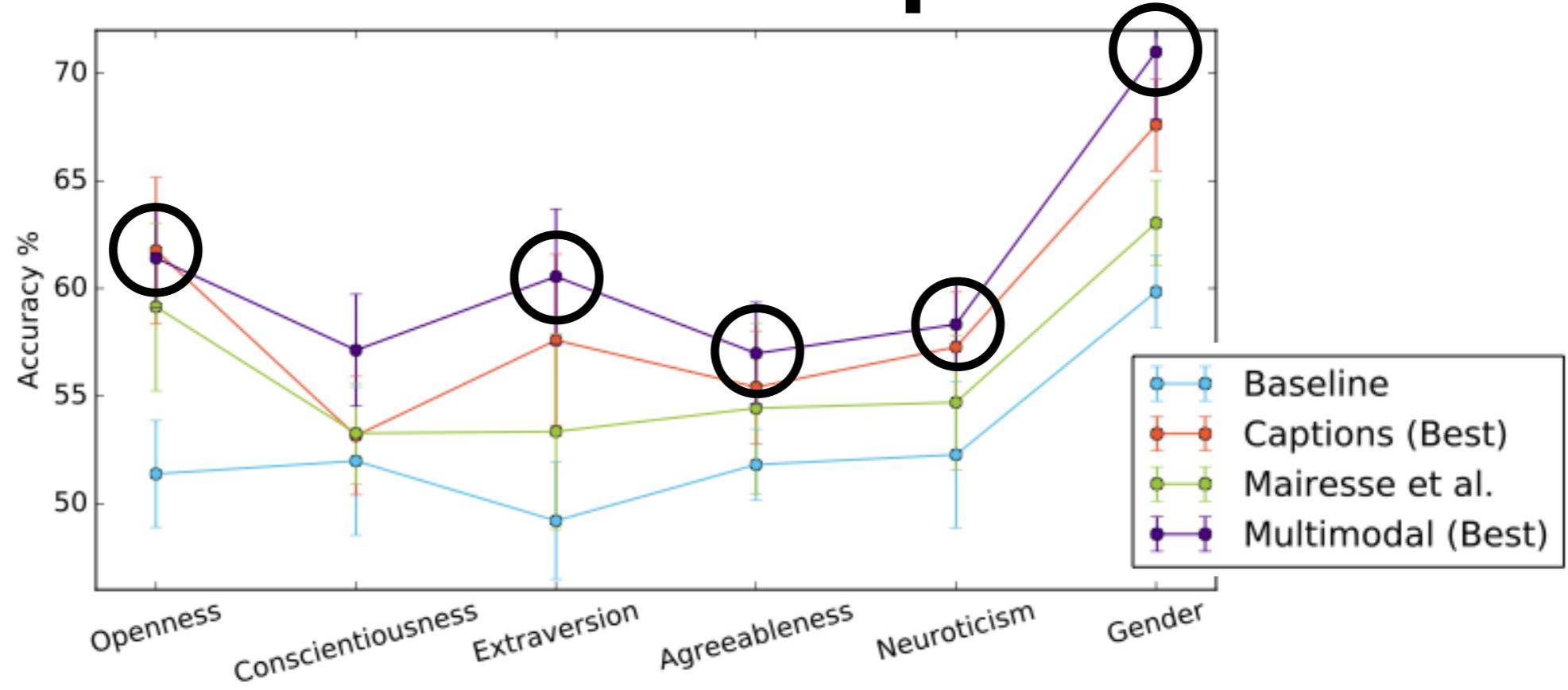


Objects: plate, fork, salad, table

Best Multimodal Model

1. Extract IEUs from each individual images
2. Combine IEUs with caption unigrams
3. Get *word2vec* embedding for each unigram
4. Average all embeddings to get feature vector

Classification Comparison



	O	C	E	A	N	Gender
Baseline	51.4±2.5	52±3.4	49.2±2.7	51.8±1.7	52.3±3.4	59.8±1.7
Captions (Best)	61.7±3.4	53.2±2.8	57.6±4.0	55.4±2.6	57.3±2.5	67.6±2.1
Mairesse et al.	59.1±3.9	53.3±2.3	53.3±4.5	54.4±4.0	54.7±3.1	63±2.0
Multimodal (Best)	61.4±2.3	57.1±2.6	60.5±3.2	57±2.4	58.3±2.1	71±3.2
Rel. Error Reduc.	5.6%	8.1%	15.4%	5.7%	7.9%	21.6%

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