A Computational & Behavioral Analysis of the Linguocultural Phenomenon of Food

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"***Language as the manifestation of human thought and behavior in a society.***"

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- By creating **numerical human judgments in the form of food norms**, we can effectively measure and predict human behavioral patterns in regard to food language use

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Make educated predictions regarding human behavior based on historical, current trends

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Contributions:

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1. Can we predict cultural information in the form of norms from linguistic information in the form of word embeddings?
2. How do corpora from different domains effect model performance?

Contributions:

Improve localization techniques, advance marketing and economic strategies, assist medical and public health sectors

Dataset & Corpora

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1. *Happy/Sad*
2. *Healthy/Unhealthy*
3. *Cheap/Expensive*
4. *Environmentally-Friendly/Environmentally-Unfriendly*
5. *Casual-Simple/Posh-Elegant*
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Socially constructed human judgment for the food item based on ingrained cultural predispositions of participants → empirically measurable ***norm*** as a numerical value

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Methods

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Advantage → Reduce sparsity of traditional vector-space representations

Disadvantage → Computationally expensive, complex algorithms i.e. neural networks

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$$\boxed{y = m + b_1 x_1 + \cdots + b_{100} x_{100}} \tag{1}$$

Goal: Infer what amount of variance in y (human score) can be explained by the dependence on x (vector)

Models

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Word2Vec was trained on all corpora with 100 dimensions, negative sampling of 5, sub-sampling of $1e-5$, a window size of 10

Model 2: Facebook fastText

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fastText was trained on all corpora with 100 dimensions, subwords of 3 to 6, 5 epochs, learning rate of 0.05

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- Categorical correlations: average correlation weaker for British participants than Chinese $\rightarrow$ higher value on *locality* for British than Chinese
- Cultural food values: British participants love *potato*, hate *horsemeat*; Chinese love *artichoke*, hate *game meat*

Distribution of Participant Scores

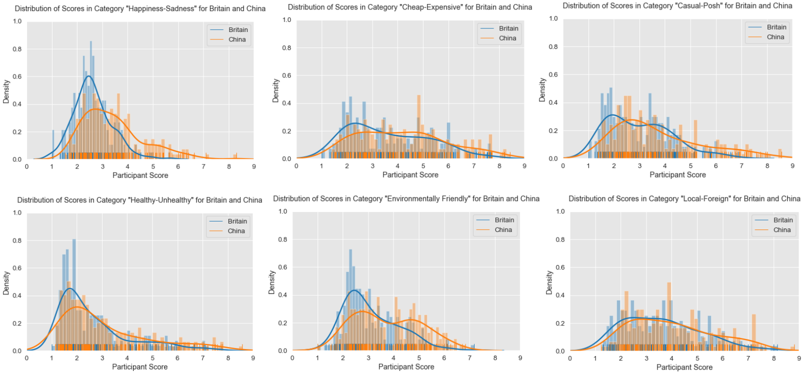

Figure: Distribution and density of British and Chinese participant scores for six evaluation categories (Example scale: 1 = happy and 9 = sad).

Correlation of Evaluation Categories

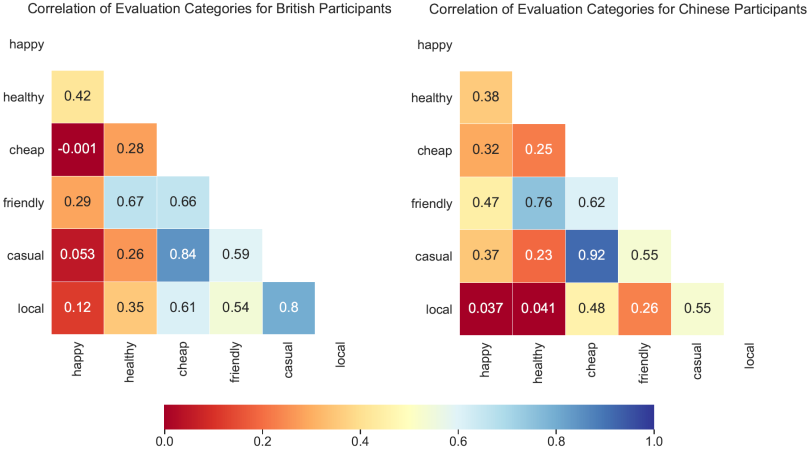

Figure: Spearman's correlation of aggregate evaluation scores for British and Chinese participants. Significant values < 0.5.

Food Scores by Country

		happy	*healthy*	*cheap*	*friendly*	*casual*	*local*
Britain	highest	strawberry	mandarin	**potato**	potherb	toast	**potato**
		1.52	1.15	1.38	1.00	1.38	1.24
	lowest	horsemeat	doughnut	caviar	veal	caviar	durian
		8.31	8.57	8.43	6.83	8.57	8.80
China	highest	quark cheese	**artichoke**	**artichoke**	**artichoke**	**artichoke**	puffed rice
		1.00	1.00	1.00	1.00	1.00	1.29
	lowest	game meat	doughnut	truffle	game meat	caviar	escargot
		5.67	7.75	7.8	7.17	6.63	8.17

Table: Highest and lowest scored food item per evaluation category for participants from Britain and China. (Ex. scale: 1 = happy, 9 = sad)

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What we find:

- Multi-linear regression model trained on food-item vectors can predict cultural norms in the form of a participant score at $r = 0.65$ and $R^2 = 0.73$ on Word2Vec vectors trained on web domain corpus

Embedding Visualization

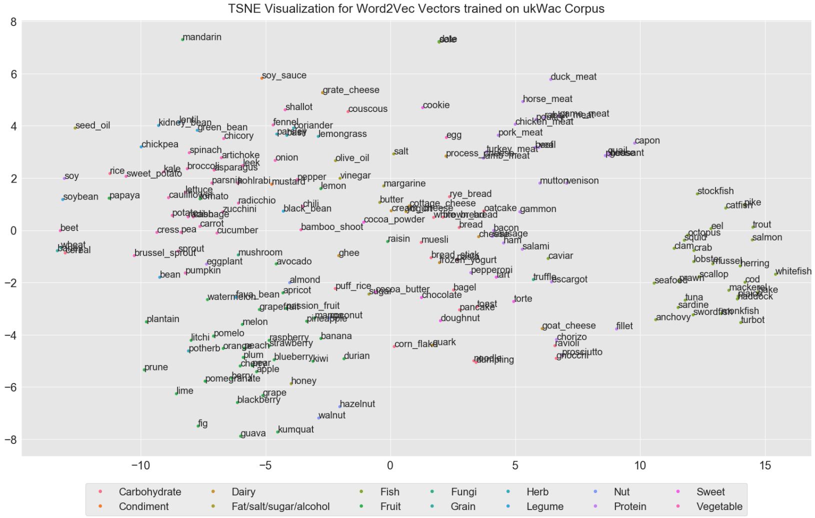

Figure: Word2Vec food norm vectors trained on UkWac web corpus.

Computational Results: Word2Vec

Word2Vec

		happy	*healthy*	*cheap*	*friendly*	*casual*	*local*	Corp. Avg.
WaCky	r	0.39	0.56	0.46	0.61†	0.45	0.55	0.50
	R^2	0.48	0.57	0.50	0.64†	0.56	0.64	0.57
Giga	r	0.36	0.58	0.56	0.63†	0.51	0.48	0.52
	R^2	0.53	0.60	0.52	0.63†	0.59	0.54	0.57
ukWaC	r	0.49	0.57	0.63	0.63	0.65†	0.60	0.59
	R^2	0.56	0.64	0.65	0.54	0.72	0.73†	0.66
Cat. Avg.	r	0.41	0.57	0.51	**0.63**	0.53	0.54	**0.53**
Cat. Avg.	R^2	0.52	0.60	0.56	**0.64**	0.62	0.64	**0.60**

Table: Multi-linear regression results for Word2Vec over six evaluation categories per corpus. Bold values indicate strongest average correlation and highest variance overall with significance above a threshold of .5. Daggers indicate strongest r or highest R^2 of individual category or domain.

Computational Results: fastText

fastText

		happy	*healthy*	*cheap*	*friendly*	*casual*	*local*	Corp. Avg.
WaCky	r	0.32	0.49	0.42	0.56†	0.37	0.51	0.44
	R^2	0.40	0.54	0.51	0.60†	0.49	0.60	0.52
Giga	r	0.44	0.65†	0.56	0.61	0.50	0.40	0.53
	R^2	0.61	0.64	0.57	0.65†	0.60	0.50	0.60
ukWaC	r	0.33	0.50	0.62†	0.61	0.53	0.53	0.52
	R^2	0.41	0.54	0.70	0.66	0.70†	0.60	0.60
Cat. Avg.	r	0.48	0.59	0.51	**0.60**	0.46	0.43	**0.49**
Cat. Avg.	R^2	0.54	0.61	0.55	**0.63**	0.56	0.54	**0.57**

Table: Multi-linear regression results for fastText over six evaluation categories per corpus. Bold values indicate strongest average correlation and highest variance overall with significance above a threshold of .5. Daggers indicate strongest r or highest R^2 of individual category or domain.

Predicted Norms: Word2Vec

Word2Vec

	happy	*healthy*	*cheap*	*friendly*	*casual*	*local*
WaCky	kidney_bean	olive_oil	kohlrabi	green_bean	wheat	bamboo_shoot
	-0.11	-4.53	-0.26	-0.03	-0.99	0.24
	catfish	brown_bread	muesli	bagel	artichoke	strawberry
	7.70	7.82	9.53	6.78	8.42	9.23
Giga	walnut	**cress**	barley	cress	spinach	cress
	0.85	-1.64	-1.99	-0.27	-2.32	-0.38
	horse_meat	cocoa_butter	gammon	turbot	**caviar**	guava
	7.65	8.57	11.35	7.30	10.10	10.55
ukWaC	orange	**pomegranate**	soy_sauce	prune	soy_sauce	oatcake
	0.50	-2.51	-0.45	-0.25	-0.66	-0.61
	quark	**cookie**	scallop	cookie	quark	**durian**
	7.17	10.37	10.36	10.63	10.92	8.76

Table: Model prediction of highest and lowest norms for Word2Vec models per corpus per category. Food items in bold indicate a correct prediction: food item is among the five highest and lowest food items evaluated by British participants (Ex. scale: 1 = happy, 9 = sad).

Predicted Results: fastText

fastText

	happy	*healthy*	*cheap*	*friendly*	*casual*	*local*
WaCky	**chocolate**	lettuce	ghee	ghee	ghee	cod
	0.15	-1.67	-1.35	0.33	-0.87	-0.75
	trout	gnocchi	fillet	**fillet**	fillet	pomelo
	6.74	7.58	11.43	8.21	10.06	9.96
Giga	apple	**apple**	cereal	**barley**	white_bread	pepper
	-1.04	-1.77	-0.45	0.48	-0.93	0.14
	goose_meat	cocoa_butter	fillet	**game_meat**	**game_meat**	eel
	7.00	8.76	9.80	7.92	9.28	8.89
ukWaC	hazelnut	kiwi	soy_sauce	mushroom	soy_sauce	mustard
	-0.79	-3.24	-0.89	1.42	-1.52	-0.08
	stockfish	**cookie**	mussel	duck_meat	mussel	stockfish
	8.13	9.02	9.91	6.44	9.46	9.54

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General Discussion

Research Answers

Answers to main research questions:

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Answers to main research questions:

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   - A multi-linear regression model trained on word representations can predict norms in the form of aggregate scores for food items at $r = 0.65$ and $R^2 = 0.73$
   - Best predicted category *Environmentally-Friendly*

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Answers to main research questions:

1. Can we predict cultural information in the form of norms from linguistic information in the form of word embeddings?
   - A multi-linear regression model trained on word representations can predict norms in the form of aggregate scores for food items at $r = 0.65$ and $R^2 = 0.73$
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2. How do corpora from different domains effect model performance?
    - Word2Vec vectors trained on web-based domain (ukWaC) elicit higher correlations than either news- or Wikipedia-based domains
    - Largest corpus, most general domain, most food-related information

Potential Drawbacks: Sense Ambiguity

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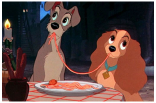

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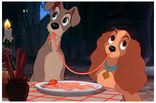

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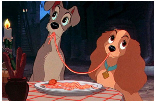

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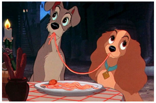


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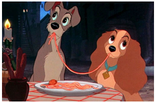

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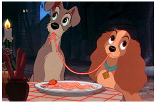

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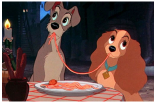

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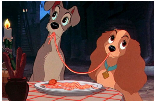


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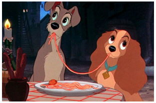


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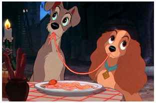


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Computational analysis of linguistic features encoded in food-word representations

- British participant norms in the form of aggregate scores for food items can be predicted from food item word representations using Multi Linear Regression
- Norm easiest to predict for participant-objective category *Environmentally-Friendly* and least predictable for participant-subjective category *Happiness-Sadness*