

# CONCEPTUAL ORGANIZATION IN THE SUPERMARKET

Adam Hornsby (@adamnhornsby), Thomas Evans, Peter Riefer, Rosie Prior & Brad Love

<https://arxiv.org/abs/1810.08577>

# **INTRODUCTION**

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...but is this **how consumers think**?

The answer helps us to optimize in-store and online search for customers

**TOMATOES ELUDE US BECAUSE...**



## TOMATOES ELUDE US BECAUSE...



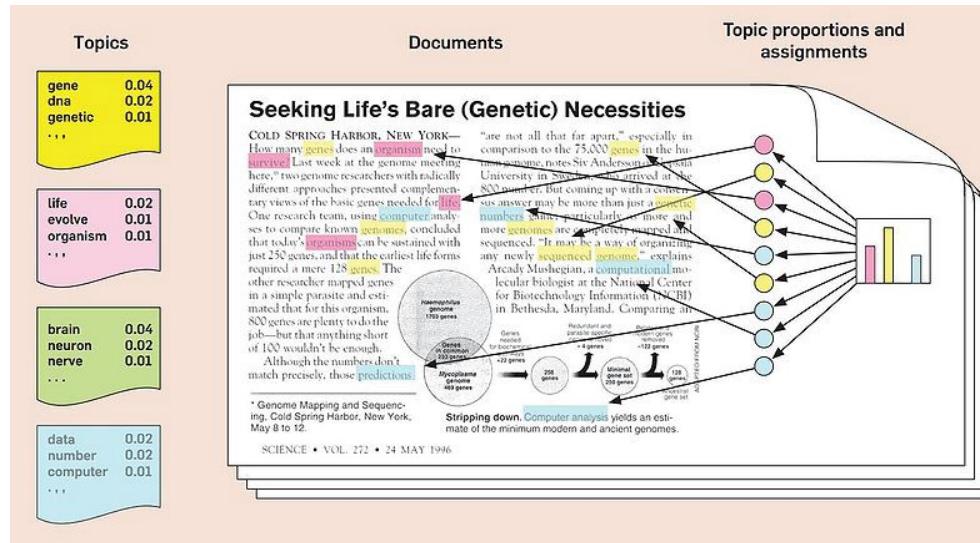
Objects gain meaning by their **interactions** with other objects (Wittgenstein, 1967, Jones & Love, 2007)

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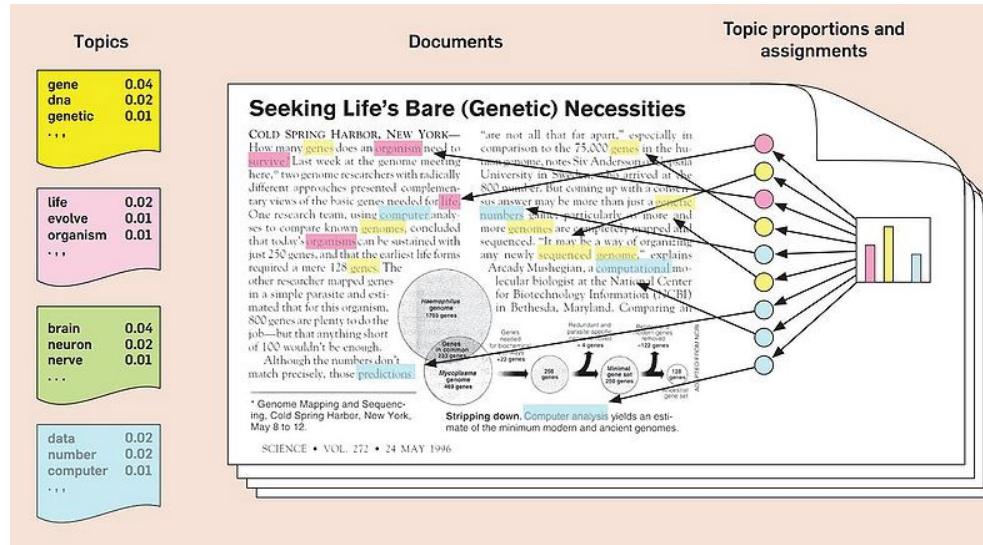


Objects gain meaning by their **interactions** with other objects (Wittgenstein, 1967, Jones & Love, 2007)  
How do people **mentally categorise** products in the supermarket?

# NLP RESEARCHERS KNOW ABOUT INTERACTIONS

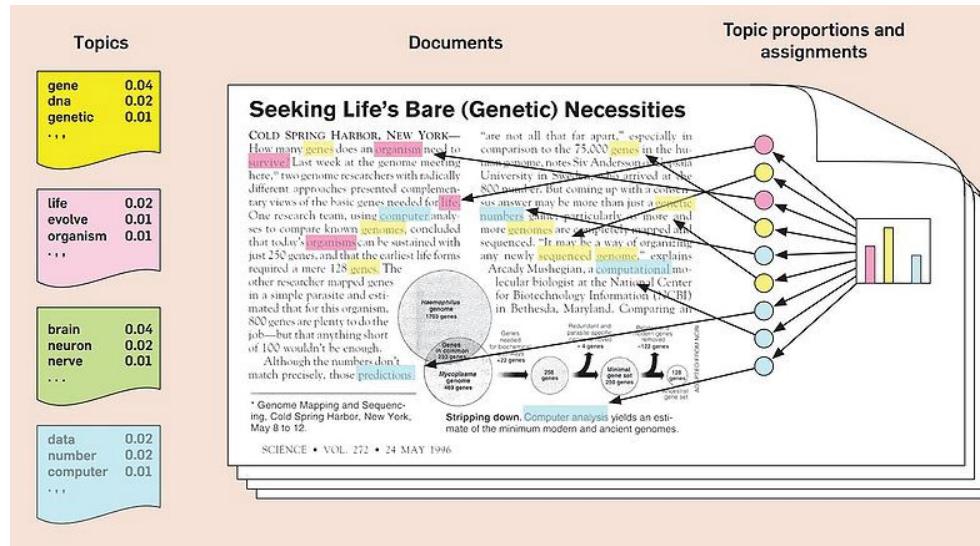


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(i.e. Distributional Hypothesis)

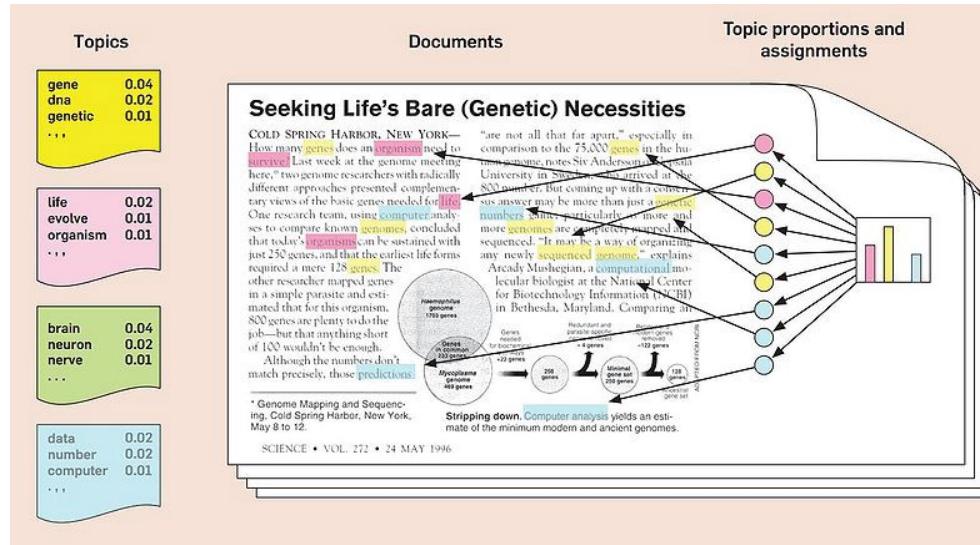
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Topic models (e.g. LDA) use this premise to learn high-level categories from language data  
So maybe these algorithms can help us to understand how consumers think about products?

# IMAGINE A BASKET INSTEAD OF A SENTENCE



Item	Count
Dog	1
Cat	0
Man	1
Bites	1
...	...



Item	Count
Chili	2
Lime	1
Milk	0
Banana	1
...	...

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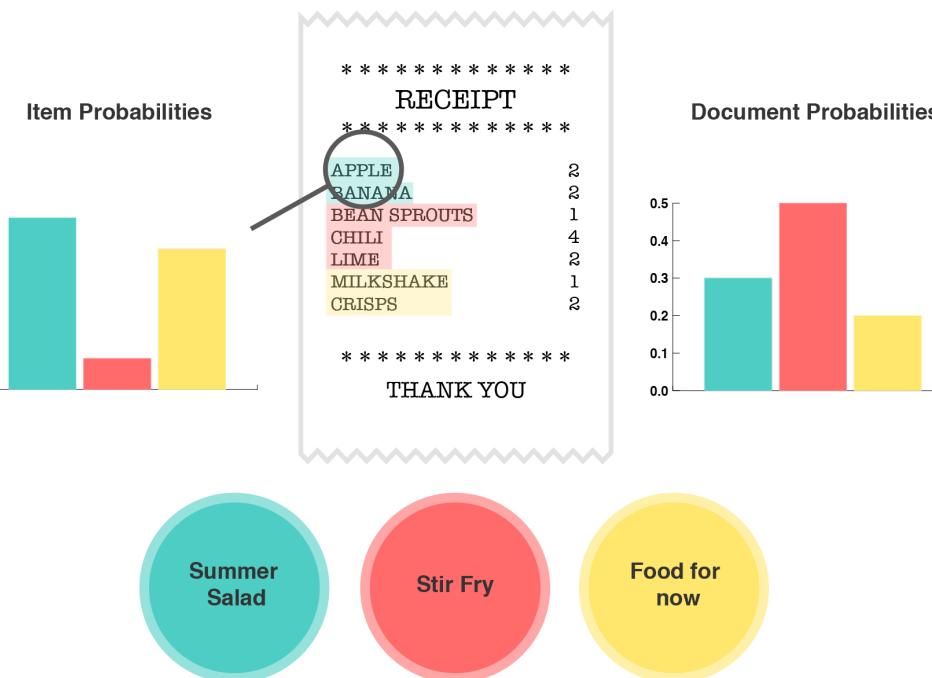
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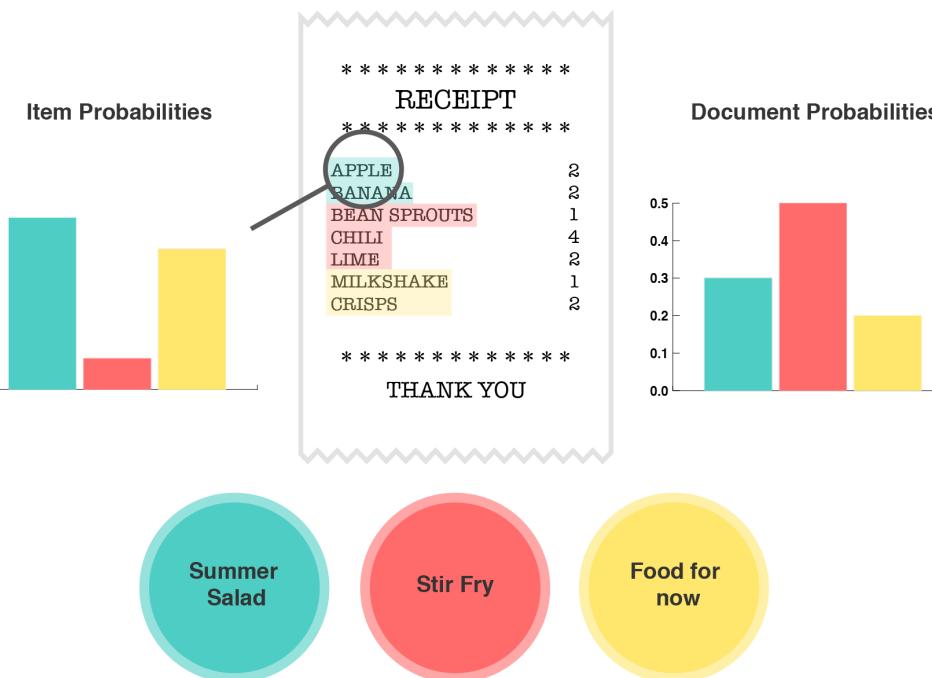
Will a topic model recover meaningful categories from basket data directly?

# **RESULTS**

# OUR TOPIC MODEL DISCOVERED SEMANTIC GROUPS

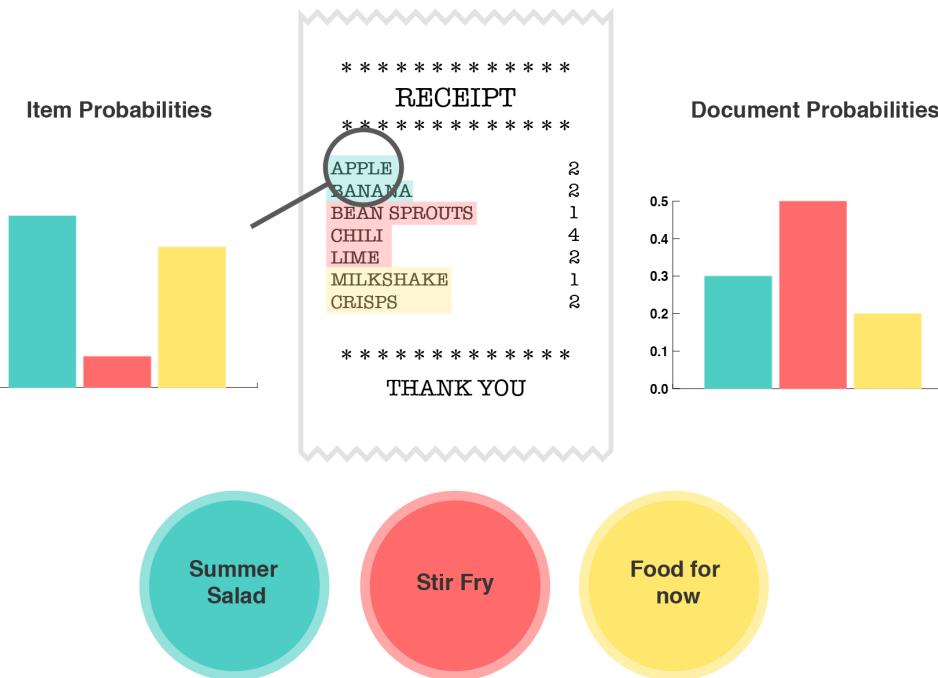


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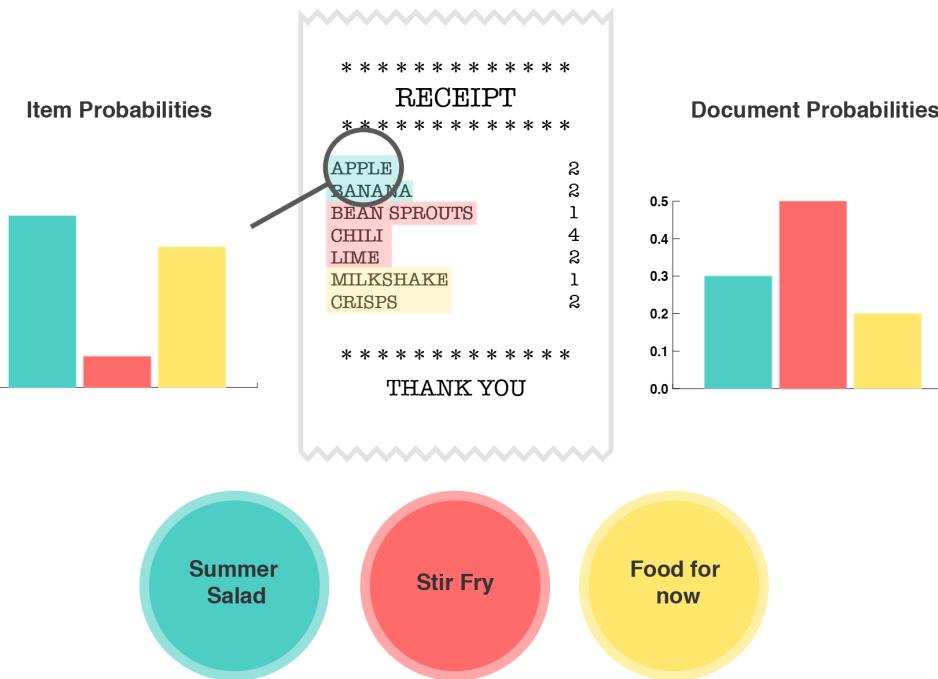
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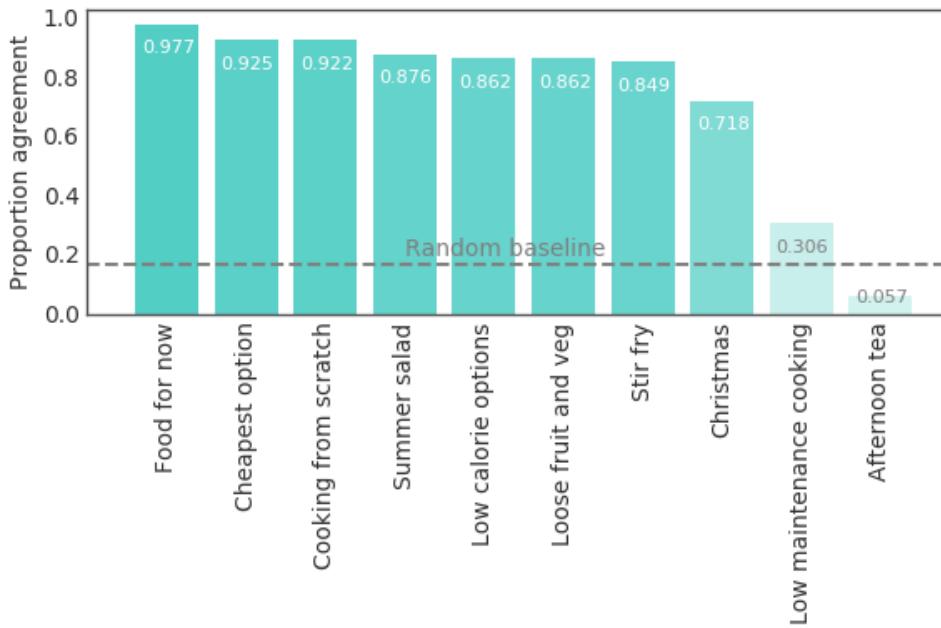
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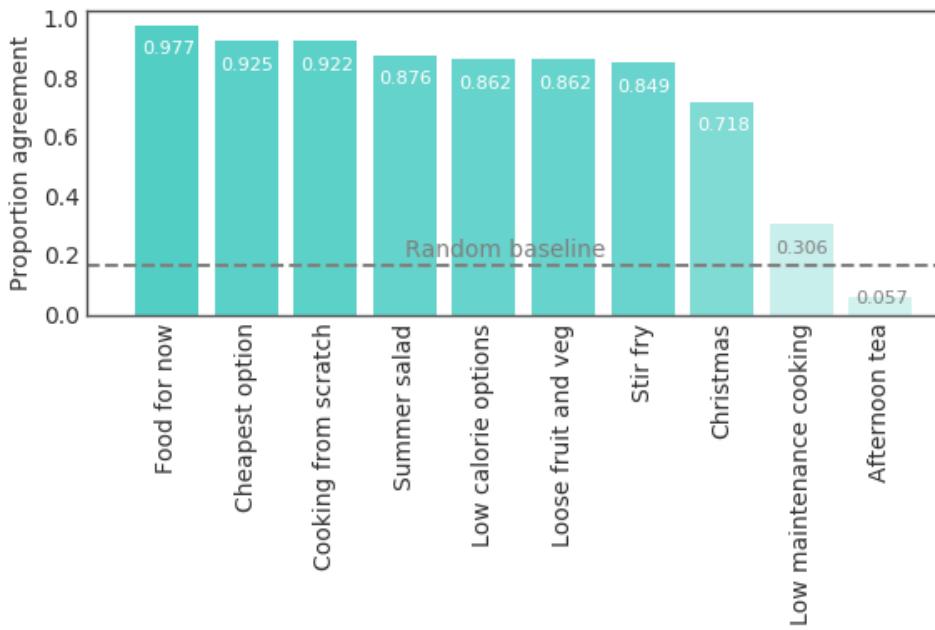
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So did they make sense to consumers?

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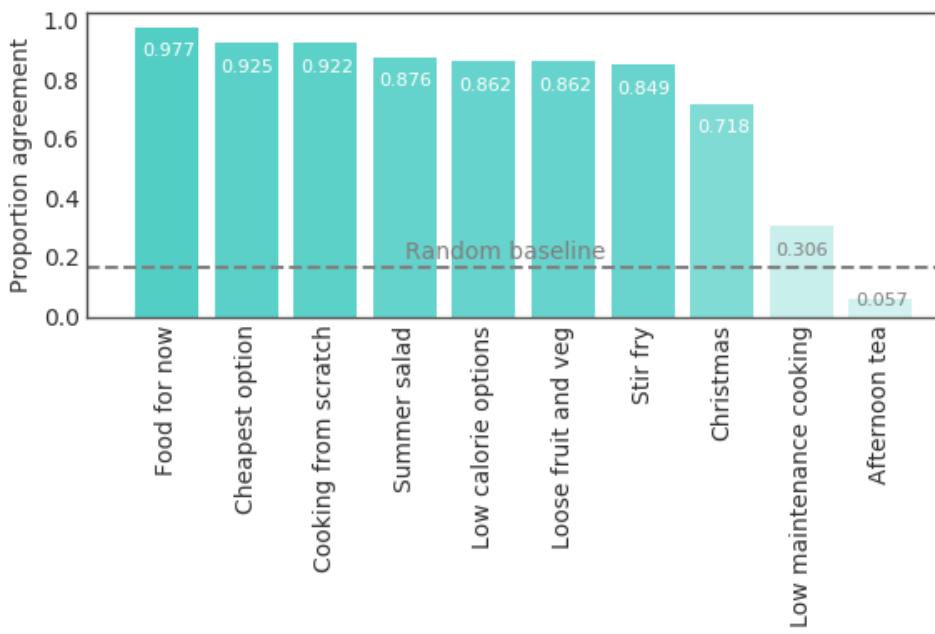


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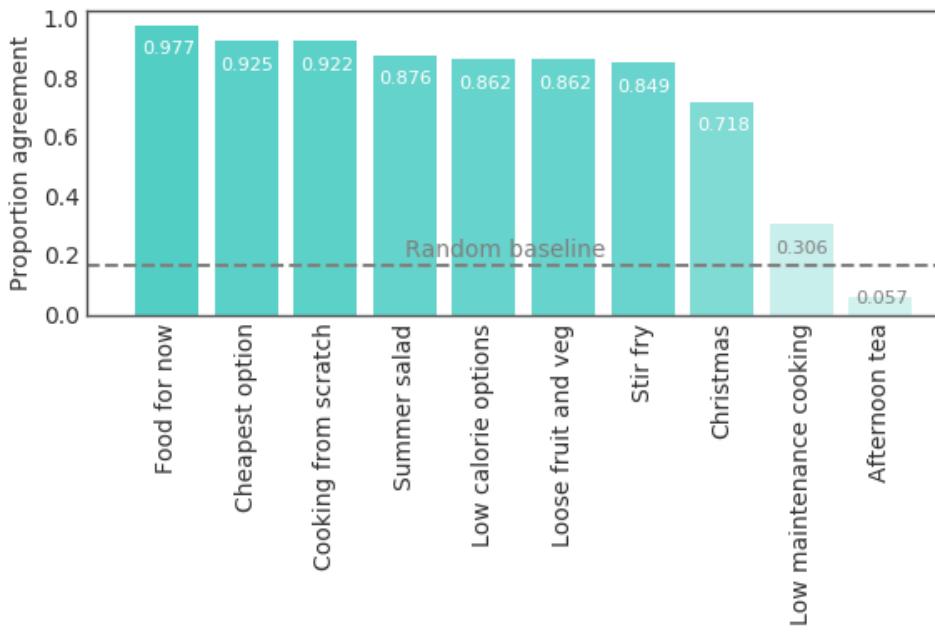
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Some were difficult (e.g. *Afternoon tea*), perhaps  
due to **individual differences**

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This can help us to personalise search algorithms

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We are using this insight to **optimize customer's routes through the store** (both online and offline) (e.g. dual siting)  
An **alternative source of data** for evaluating NLP models  
(data & code available soon)

# Conceptual Organization is Revealed by Consumer Activity Patterns

Adam N. Hornsby<sup>a,b</sup>, Thomas Evans<sup>a</sup>, Peter S. Riefer<sup>a</sup>, Rosie Prior<sup>a</sup>, and Bradley C. Love<sup>b,c,1</sup>

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