# Quantifying cronuts: Predicting the quality of blends

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#### I. Introduction

## Calling all innovators

Linguistic innovation is hard



## Calling all innovators

- We don't have to make an entirely new word happen
- Anyone can blend existing ones



**BRO** 

+ ROMANCE



# **BROMANCE**

## **FRIEND**

#### +

## **ENEMY**



# **FRENEMY**

**HORSE** 

+

CORGI



HORGI

## **FRIENDS**

#### +

## **FAMILY**



## FRAMILY???

#### Some blends are better than others

#### Questions to answer:

- 1. What makes some blends better than others?
- 2. How can we predict which blends people will understand and like?

#### Our approach:

- 1. Collect ratings of blends
- 2. Build a model of what people do
- 3. Identify the predictors that matter
- 4. (In progress) Extend to rating new blends

## II. An ontology of blends

## A working definition

For the purpose of this study, a blend:

- 1. Is a linear combination of two source words
- 2. Uses overlap and/or truncation at the point of blending

#### Non-blends:

- 1. Compounds without truncation: manspreading
- 2. Libfixes: work-aholic, gamer-gate, lumber-sexual

#### Blend classes

- Complete overlap: Source words overlap in output, all of each source word appears
   alcoholiday guesstimate mathlete
- 2. Partial overlap: Source words overlap in output, but not all sounds are preserved affluenza brony facon sext shitticism
- 3. No overlap: No segmental overlap, but some truncation at combination point cosplay sharknado shotchka zonkey

## Selecting items

#### Chosen from:

- Wikipedia portmanteau list
- Thurner portmanteau dictionary
- Listening for everyday occurrences

#### Excluded:

- Brand names
- Unclear analysis (keytar, murse)

## III. Quantifying blends

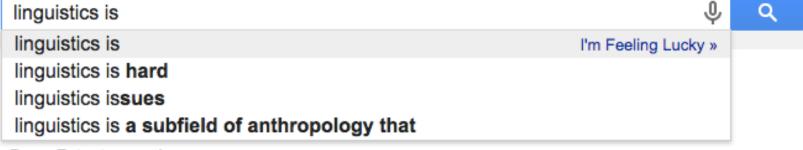
## Defining the source-output relationship

- 1. Amount of phonological content present
  - e.g., Gries 2004
- 2. Phonological wellformedness
  - e.g., Kelly 1998
- 3. How easily the source words can be identified using the output content

#### Identifying source from partial content

- In speech processing: cohort effects (e.g., Marslen-Wilson 1987)
- In layperson's terms: autocomplete





Press Enter to search.

#### affluence + influenza = affluenza

```
Segment content ratios (r1, r2):

affluen / affluence fluenza / influenza

Identification probability (p1, p2):

p(affluence | affluen-) p(influenza | -fluenza)
```

<sup>\*</sup>All computations are over segments; orthography shown for convenience

#### Computing identification probability

#### (Fake) example:

p2 = .43

```
language + debate = langbate

lang- = L AE NG

Competitors: language (.99), languid (.006), languish (.004)

p1 = .99

-bate = B EY T

Competitors: bait (.45), debate (.43), masturbate (.06),

rebate (.01)...
```

Pronunciations from CMUdict (modified), SUBTLEX-US frequencies

## Some harder to quantify factors

- Orthographic disambiguation: fauxhawk helped by x when written (not confusable with focus, folk, etc.)
- Semantic restrictions: cronut, labradoodle helped by restriction on what could possibly be combined
- Phonological problems: coatigan creates flapping context, rawnola creates stress clash



#### Some even harder to quantify factors

- Stress/metrical structure: surely contribute to choice of output form among alternatives, but it's not straightforward
  - How much does the stress on tornado improve sharknado?
  - If syllable structure is respected, where'd the d go in frenemy?
- Plausibility: does the blend make any sense? What's a mirthquake?

#### IV. Results

#### Survey design

- Chose 88 attested blends that were likely to be understood but varied in apparent quality
- Participants (n=34) rated each blend on two scales:
  - 1. Understandability: Is it easy to understand what words make up this blend?
  - 2. Naturalness: Does this combination of words sound natural to you?
- Could answer: "Didn't understand" or on scale:
   Terrible Poor Fair Good Excellent
- Expected high correlation between understandability and naturalness; our interest was in the outliers

#### Best and worst blends

#### Most understandable:

Blend	Source words	Average rating (1-5)
mathlete	math + athlete	4.8
sexpert	sex + expert	4.8
guesstimate	guess + estimate	4.8

#### **Least understandable:**

fozzle	fog + drizzle	1.8	
mizzle	mist + drizzle	2.3	
brinkles	bed + wrinkles	2.3	

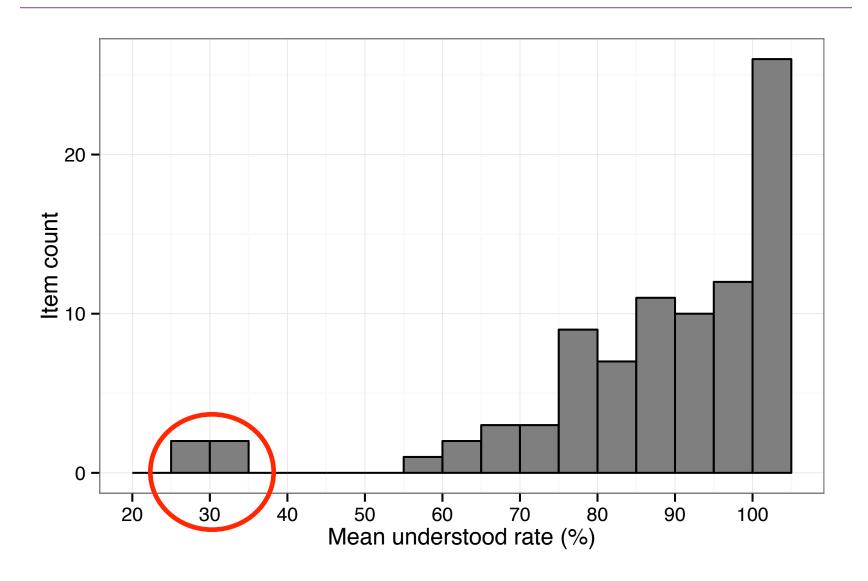
#### **Most natural:**

sexpert	sex + expert	4.8
mockumentary	mock + documentary	4.7
guesstimate	guess + estimate	4.7

#### **Least natural:**

dunch	dinner + lunch	2.1
nukemare	nuke + nightmare	2.2
rawnola	raw + granola	2.3

## Item mean rates of understanding



## Rarely-understood blends

#### **Least understood:**

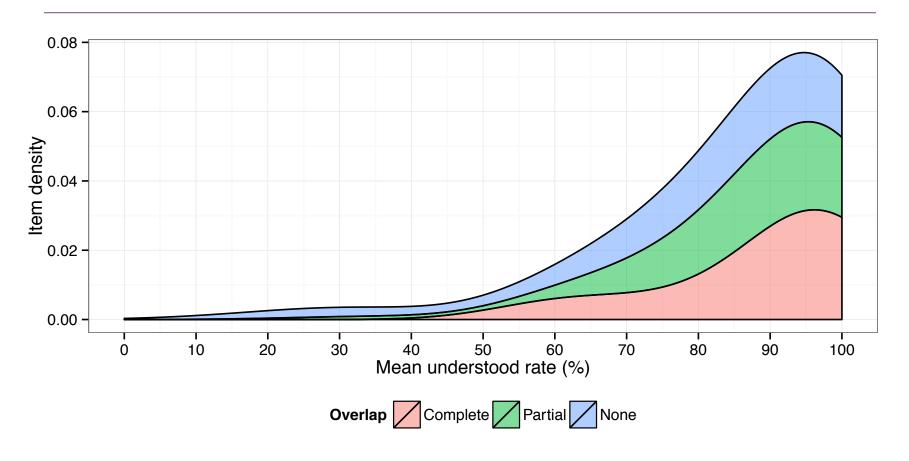
fozzle	fog + drizzle	26%
wonut	waffle + donut	28%
brinkles	bed + wrinkles	31%
mizzle	mist + drizzle	34%
wegotism	we + egotism	58%



#### Item types

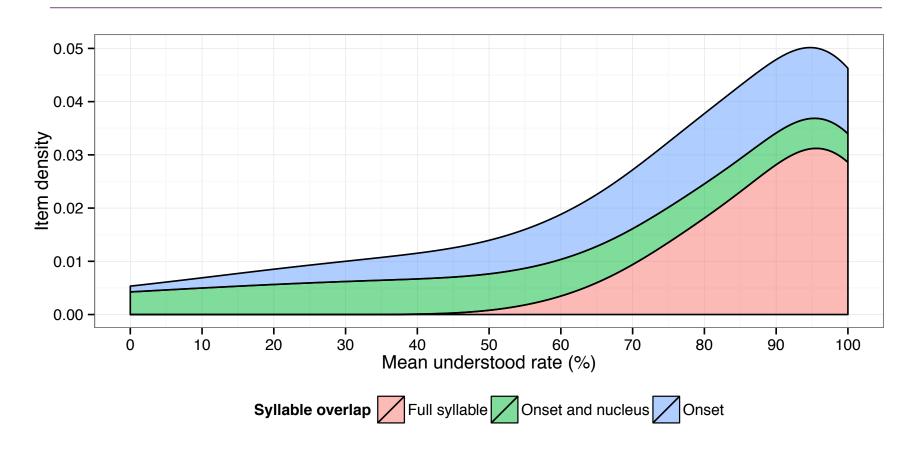
- Source word overlap (complete, partial, or none)
  - Hypothesis: complete overlap leads to the best blends
- First syllable overlap
  - Hypothesis: if there isn't enough of the syllable structure of the first word, it's hard to recover (above and beyond what segments tell us)
  - Levels of first syllable of first word present:
    - Onset
    - Onset and nucleus
    - Full first syllable

#### Overlap type



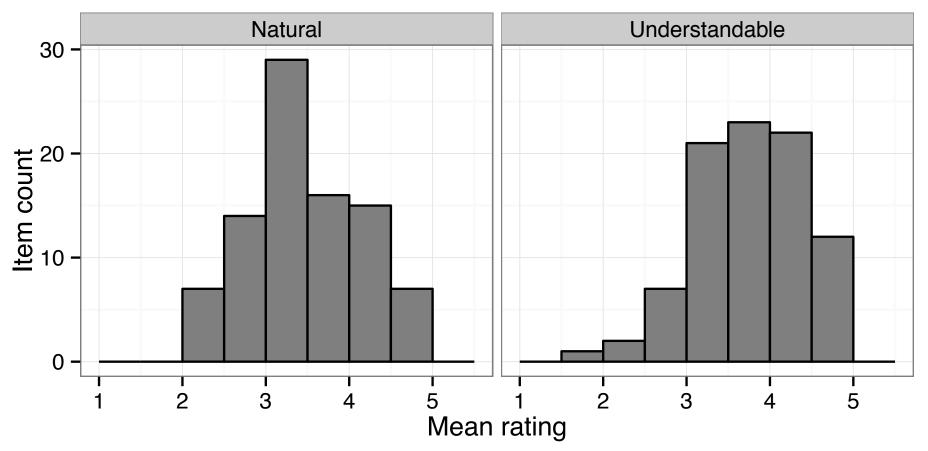
Overall little difference in understandability by overlap type

## Syllable overlap type



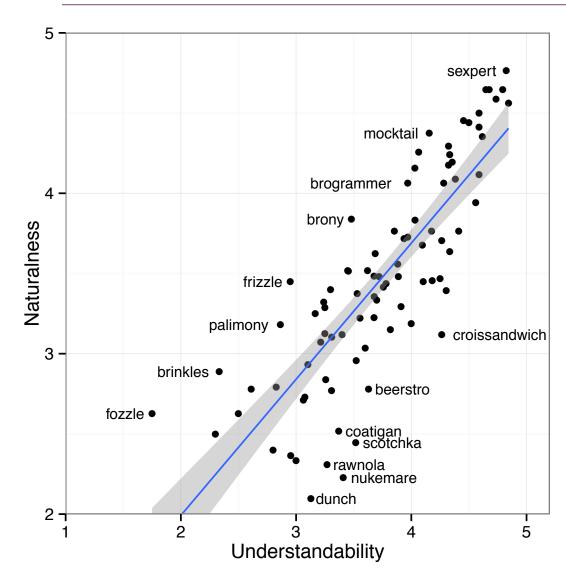
Full syllable overlap helps with understanding, but there's little differentiation between just onset and onset and nucleus

## Item mean understandability/naturalness



Items rated more understandable than natural, understandable ratings skew high

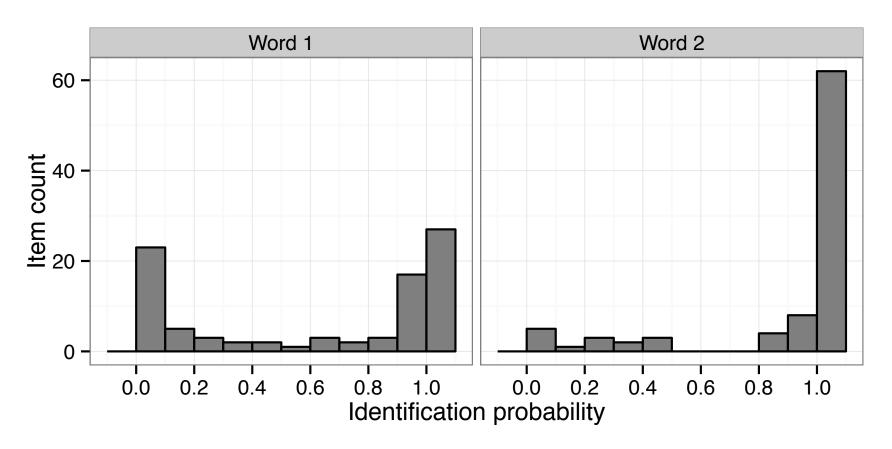
## Ratings correlations



**Above**: more natural than understandable. Often minimal edits from real words.

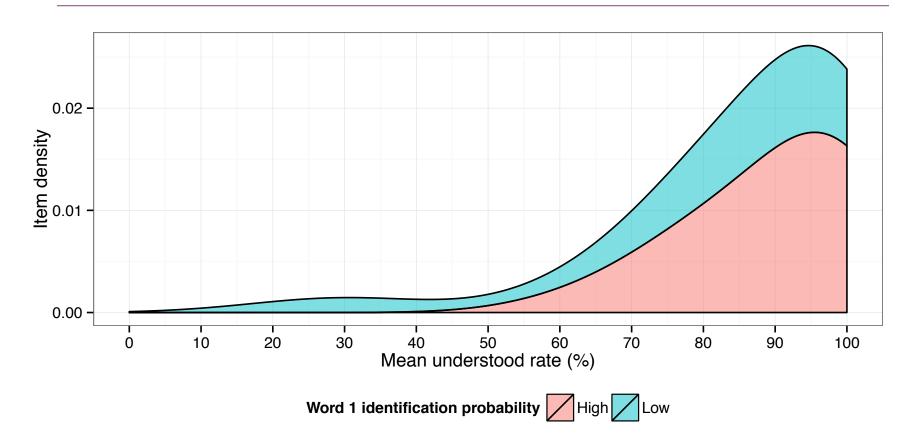
Below: can be understood, but unnatural. Marketing/branding: beerstro coatigan croissandwich rawnola

## Distribution of identification probability



Word 1 has very high/low ID prob., Word 2 at ceiling

## High and low identification probability

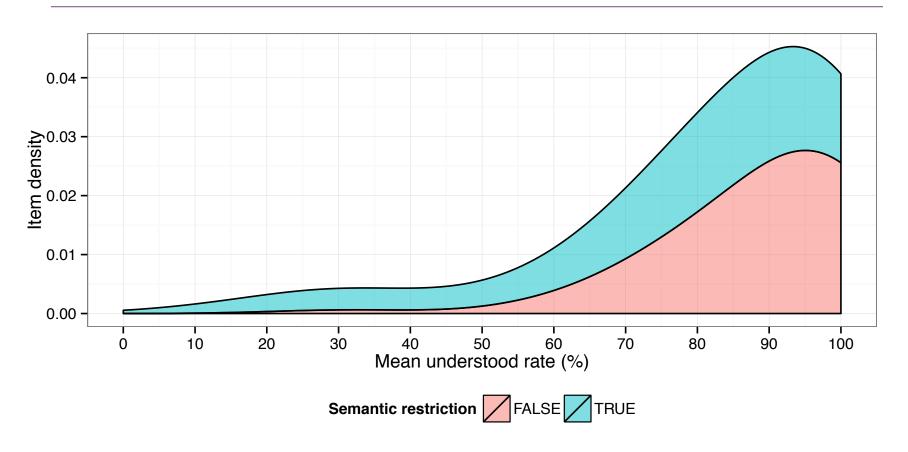


Low word 1 identification probability (< 0.5) is indicator of low rate of understanding

## Modeling understandability

- Used cumulative-link mixed-effects models to model ratings, assess significance by Chisq. LL ratio test
  - No interval assumption or normality assumption
- Significant effect of first (p = 0.003) and second (p = 0.009) ID prob. on understandability
  - Each doubling of ID prob. → 15% chance of higher rating for word 1, 30% chance of higher rating for word 2
- ID probs. stronger predictor than segment ratios (better log-likelihood/AIC/BIC)
- Same pattern holds for modeling whether an item was understood as a binary response

#### Semantic domain restriction



Less-understood items are more likely to have a restriction (e.g., source words must be foods); this probably makes otherwise unacceptable blends tolerable.

#### V. Conclusion

#### Summary

- First human subjects study evaluating blend quality
- Identified properties of bad blends:
  - Less overlap
  - Little phonological content carried over from first word
- Good blends, however, come in all kinds
- Found reliable effect of identification probability on ratings
  - Suggests statistical processing effects on blend reconstruction
- Not yet able to model other blend domains
  - Personal names (Kimye, Bennifer), featural overlap (hangry)

#### Modeling blend choice

- We had subjects rate attested blends and modeled their ratings
  - Possible improvements: model continuous levels of semantic relatedness, part-of-speech matching between source words
- Next step is modeling the blend point of a given source word pair: why frenemy and not frendemy or fenemy?
- Proposal: model blend choice as binary classification
  - Positive examples are attested blends (frenemy)
  - Negative examples are unattested alternates (frendemy, fenemy)
  - Similar to Maxent OT or Harmonic Grammar

#### Further human subjects experiments

- Test impact of domain restriction on reconstruction ability
- Ask participants to give source words for a blend with or without the semantic domain
- Example:

What words are put together to make fozzle?

**Hint**: They're weather-related

#### Thanks!

#### References

Gries, S. Th. (2004). Shouldn't it be breakfunch? A quantitative analysis of blend structure in English. *Linquistics* 42(3): 639–667.

Kelly, M. H. (1998). To "brunch" or to "brench": some aspects of blend structure. *Linguistics* 36(3): 579–590.

#### **Blend sources:**

http://en.wikipedia.org/wiki/List\_of\_portmanteaus

Thurner, D. (1993). Portmanteau dictionary: blend words in the English language, including trademarks and brand names. Jefferson, North Carolina: McFarland and Company.

#### On libfixes vs. blends:

#### Zwicky:

http://arnoldzwicky.org/category/morphology/libfixes/

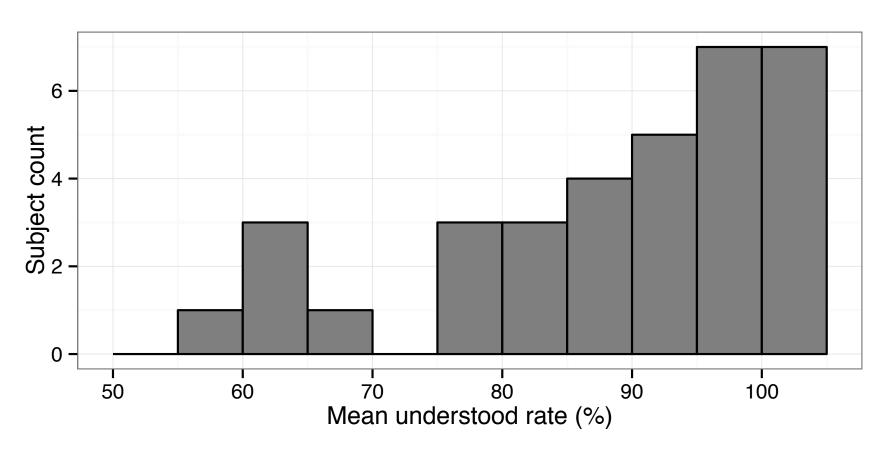
#### Gorman:

http://sonny.cslu.ohsu.edu/~gormanky/blog/defining-libfixes/



#### Additional slides

#### Subject variation



Cluster of five subjects said they didn't understand more than 30% of items