Data Science Applications

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Recipe difficulty tagger

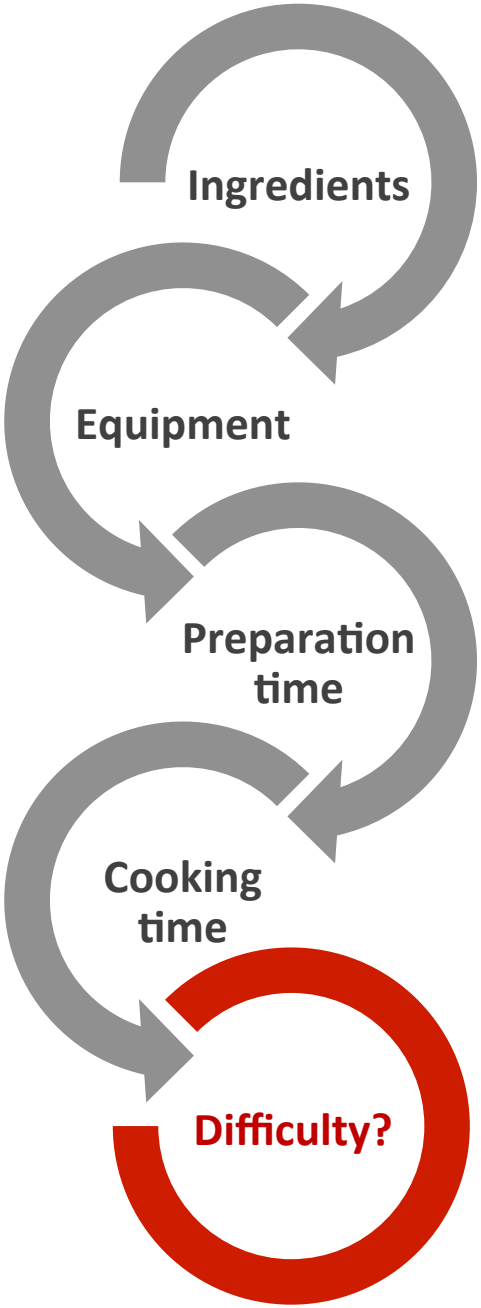
Building a Menu Planner Helper App

Menu Planning & Preparation






Multiple Chefs | Multi-tasking



Not all recipes are created equal

- How can we simplify planning & cooking?
- What aspects of a recipe make it challenging?
- **Can we classify recipes by their "difficulty"?**

**very few sites/books include this info.

Creating & Using a recipe-difficulty-tagger

Data & Pre-processing

- **Scraped ≈10,100 recipes + info.** from **BBCgoodfood.com**
- ***New York Times* CRF—recipe-phrase-tagger** : teasing out '***ingredient***' words & excluding ***quantity /units***
- **NLP | Tokenization:** creating word tokens for each recipe

Topic Modeling & Classification:

- **Topic-modeling : Latent Dirichlet Allocation (LDA)**
  -- LDA transformed matrices yield dimensionality reduced probabilistic topic-word-associations
  - Ingredients
  - Instructions
- $\beta_1 LDA_{ingredients} + \beta_2 LDA_{instructions} + \beta_3 prep_{time} + \beta_4 cook_{time} + \beta_5 N_{ingredients} \approx$ **"difficulty" ?**

Post-tagging Usage:

- **K-NearestNeighbours** on $LDA_{ingredients}$
  - **find K similar recipes based on ingredients**
- **For a given recipe:**
  - what are **other similar recipes**?
  - what are **other recipes' "difficulty" class**?

NYT-ingredient phrase tagger

- The model predicts ***sequences of labels*** for ***sequences of words***.
- ~ Parts-Of-Speech-tagging | Named-Entity-tagging
- 89% sentence-level accuracy when trained on 130,000 labeled ingredient phrases.

Example

Ingredient Phrase	1	tablespoon	fresh	lemon	juice
Ingredient Labels	QUANTITY	UNIT	COMMENT	NAME	NAME

predict NAME, UNIT, QUANTITY, COMMENT and OTHER.

Examples

INPUT	NAME	QUANTITY	UNIT	COMMENT
1 6-inch white-corn tortilla	white-corn tortilla	1.0		6-inch
3 cups seedless grapes, equal amounts of red and green grapes	grapes	3.0	cup	seedless, equal amounts of red and green
1/4 cup good quality olive oil	good quality olive oil	0.25	cup	
3 large cloves garlic, smashed	garlic	3.0	clove	smashed
Rind from 1/2 pound salt pork	salt pork	0.5	pound	Rind from

Tagged ingredient phrases

```
250gram dark-chocolate
2 tablespoon golden syrup
568milliliter carton double cream
4 teaspoon instant coffee granules
1 teaspoon ground cinnamon
cocoa powder, for dusting
```

bbcgdfd_469o.txt

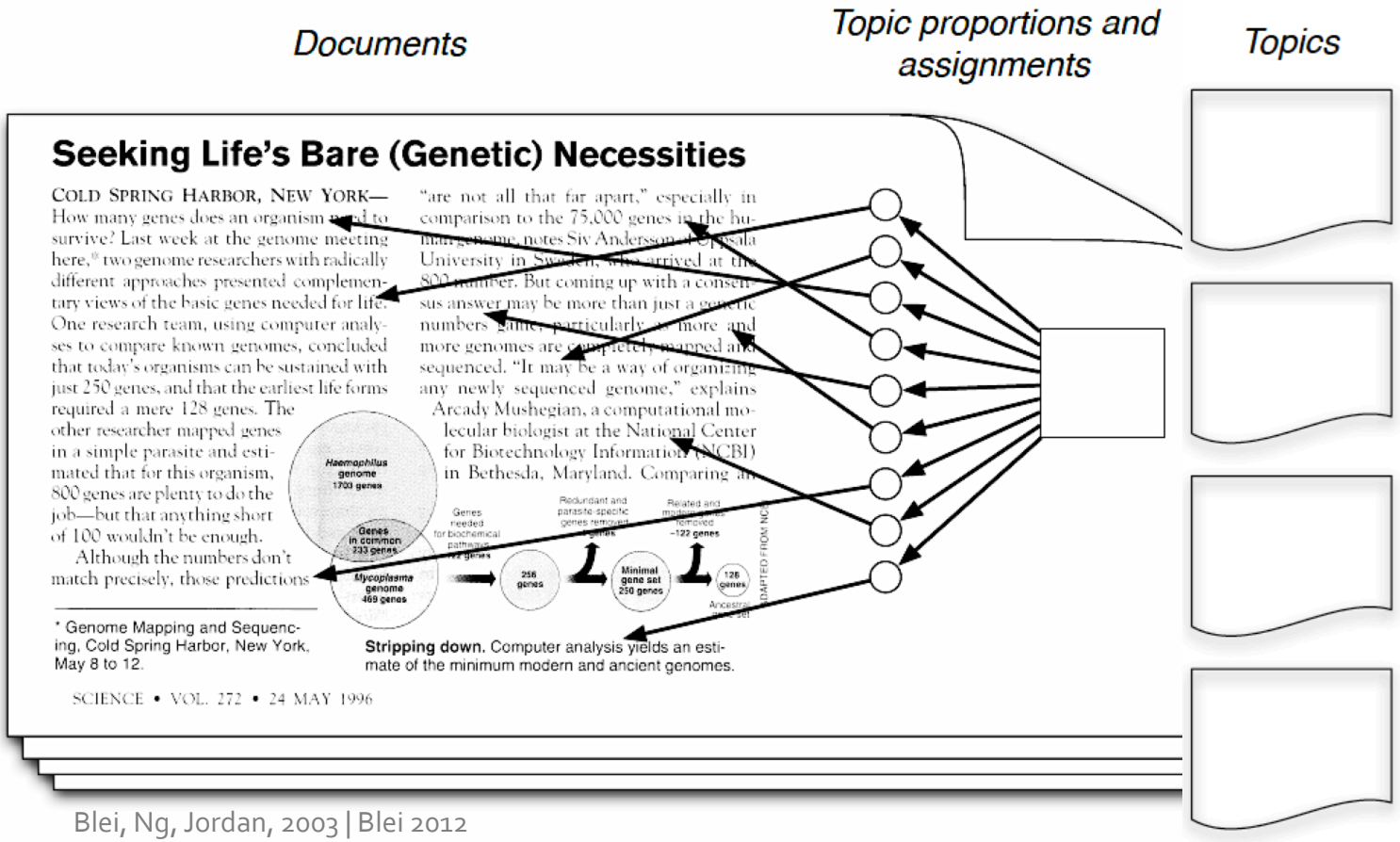
```
# 0.774212
250gram I1      L4      NoCAP   NoPAREN B-QTY/0.826164
dark-chocolate  I2      L4      NoCAP   NoPAREN B-NAME/0.871789

# 0.841936
2       I1      L8      NoCAP   NoPAREN B-QTY/0.989355
tablespoon      I2      L8      NoCAP   NoPAREN B-UNIT/0.979152
golden  I3      L8      NoCAP   NoPAREN B-NAME/0.867876
syrup   I4      L8      NoCAP   NoPAREN I-NAME/0.879950

# 0.238208
568milliliter   I1      L8      NoCAP   NoPAREN B-QTY/0.753478
carton  I2      L8      NoCAP   NoPAREN B-UNIT/0.301439
double  I3      L8      NoCAP   NoPAREN B-NAME/0.549777
cream   I4      L8      NoCAP   NoPAREN I-NAME/0.873516
for     I4      L8      NoCAP   NoPAREN B-COMMENT/0.857110
dusting I5      L8      NoCAP   NoPAREN I-COMMENT/0.965766
```

	input	name	other	qty	unit	qty1	unit1	name1	comment
0	250gram dark-chocolate	dark-chocolate	NaN	250gram	NaN	*250*	*gram*	*dark-chocolate*	*NaN*
1	2 tablespoon golden syrup	golden syrup	NaN	2	tablespoon	*2*	*tablespoon*	*golden syrup*	*NaN*
2	568milliliter carton double cream	double cream	NaN	568milliliter	carton	*568*	*milliliter*	*double cream*	*NaN*
3	4 teaspoon instant coffee granules	instant coffee granules	NaN	4	teaspoon	*4*	*teaspoon*	*instant coffee granules*	*NaN*
4	1 teaspoon ground cinnamon	cinnamon	NaN	1	teaspoon	*1*	*teaspoon*	*cinnamon*	*ground*
5	cocoa powder, for dusting	cocoa powder	,	NaN	NaN	*NaN*	*NaN*	*cocoa powder*	*for dusting*

LDA topic-modeling

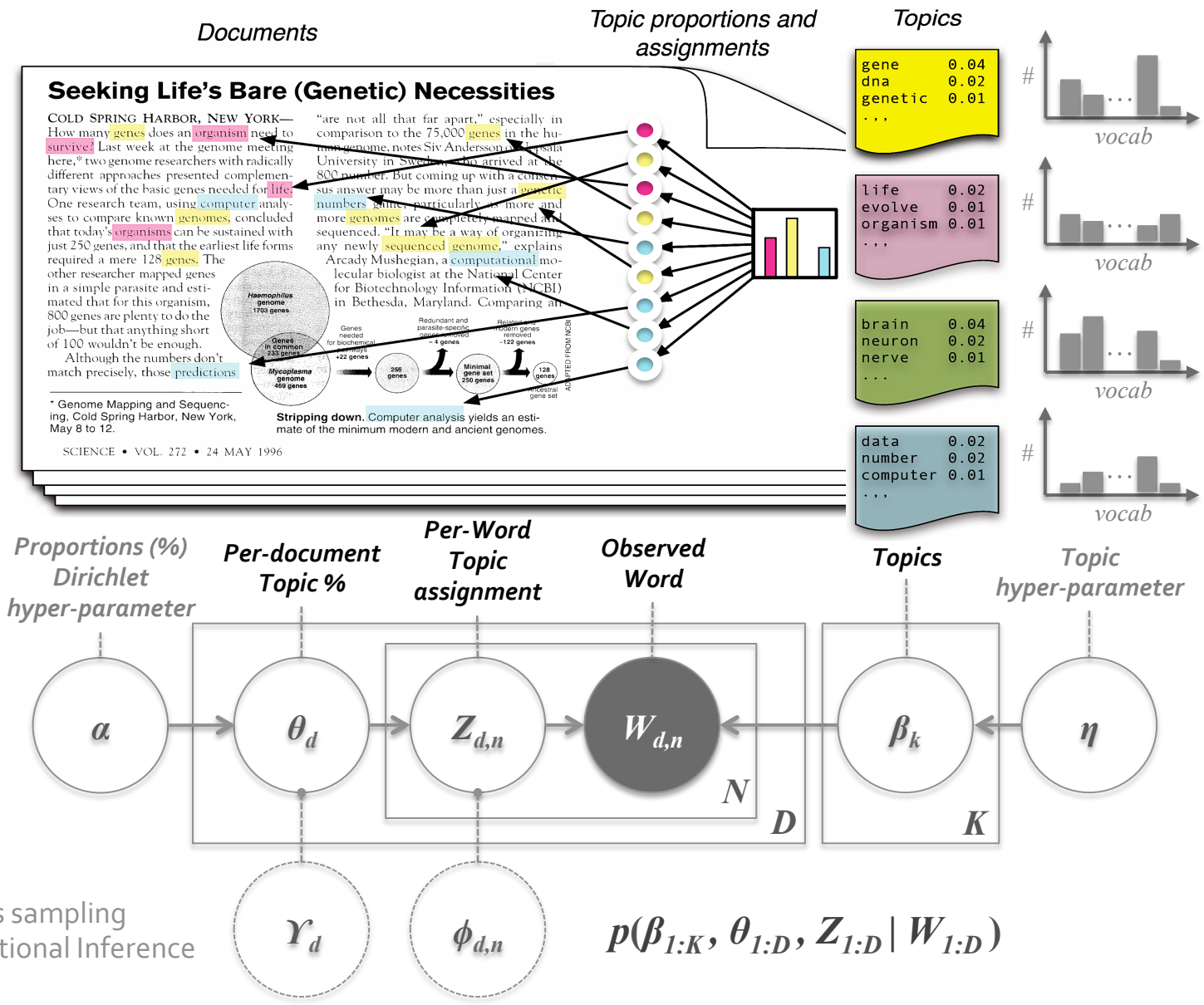


Blei, Ng, Jordan, 2003 | Blei 2012

Infer the hidden topic structure from observed documents

→ **Reversing the generative process**…

An intuition – text generation

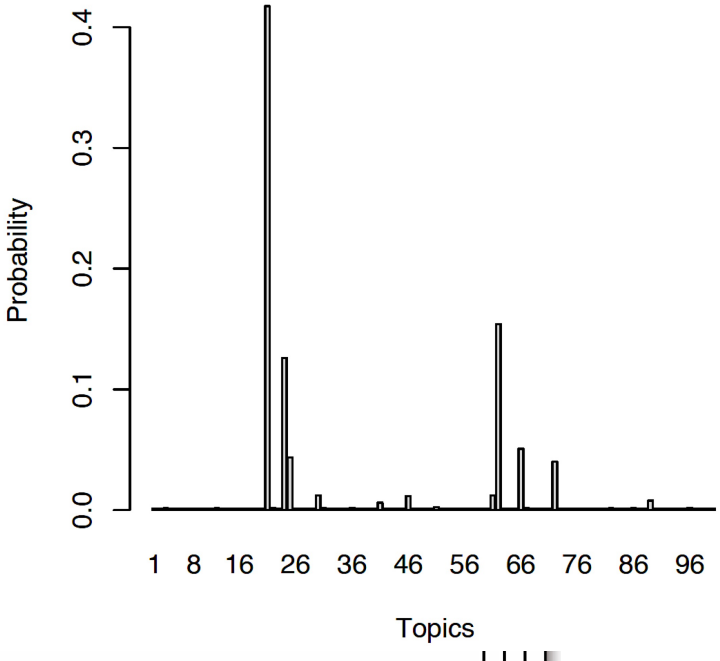


- Gibbs sampling
- Variational Inference

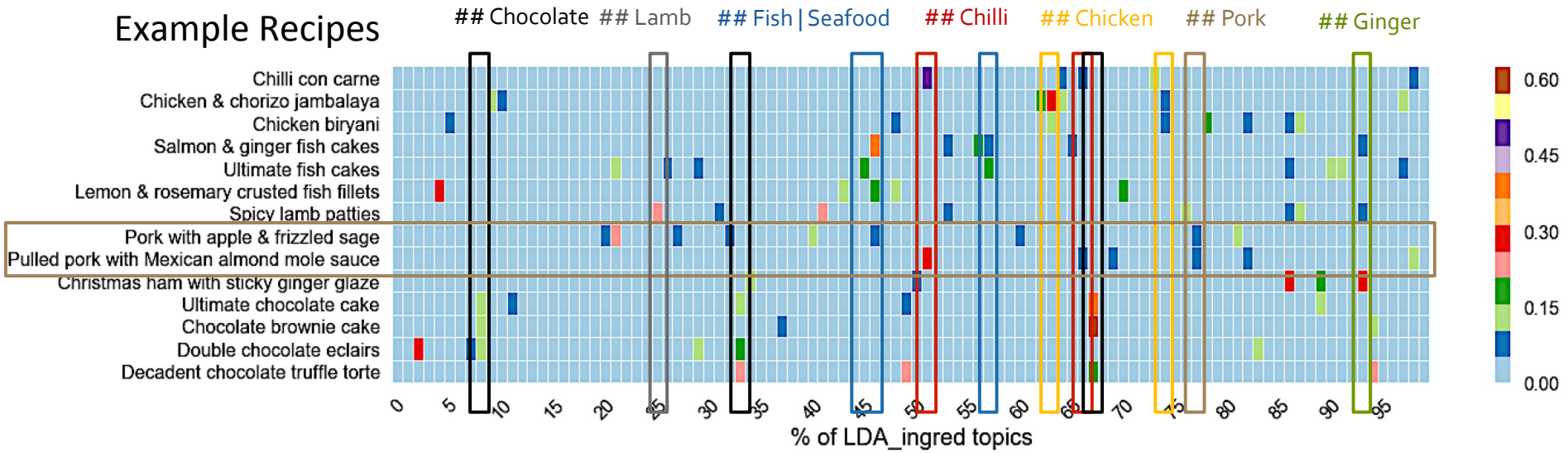
LDA topic-modeling

Seeking Life's Bare (Genetic) Necessities

"Genetics"	"Evolution"	"Disease"	"Computers"
human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations



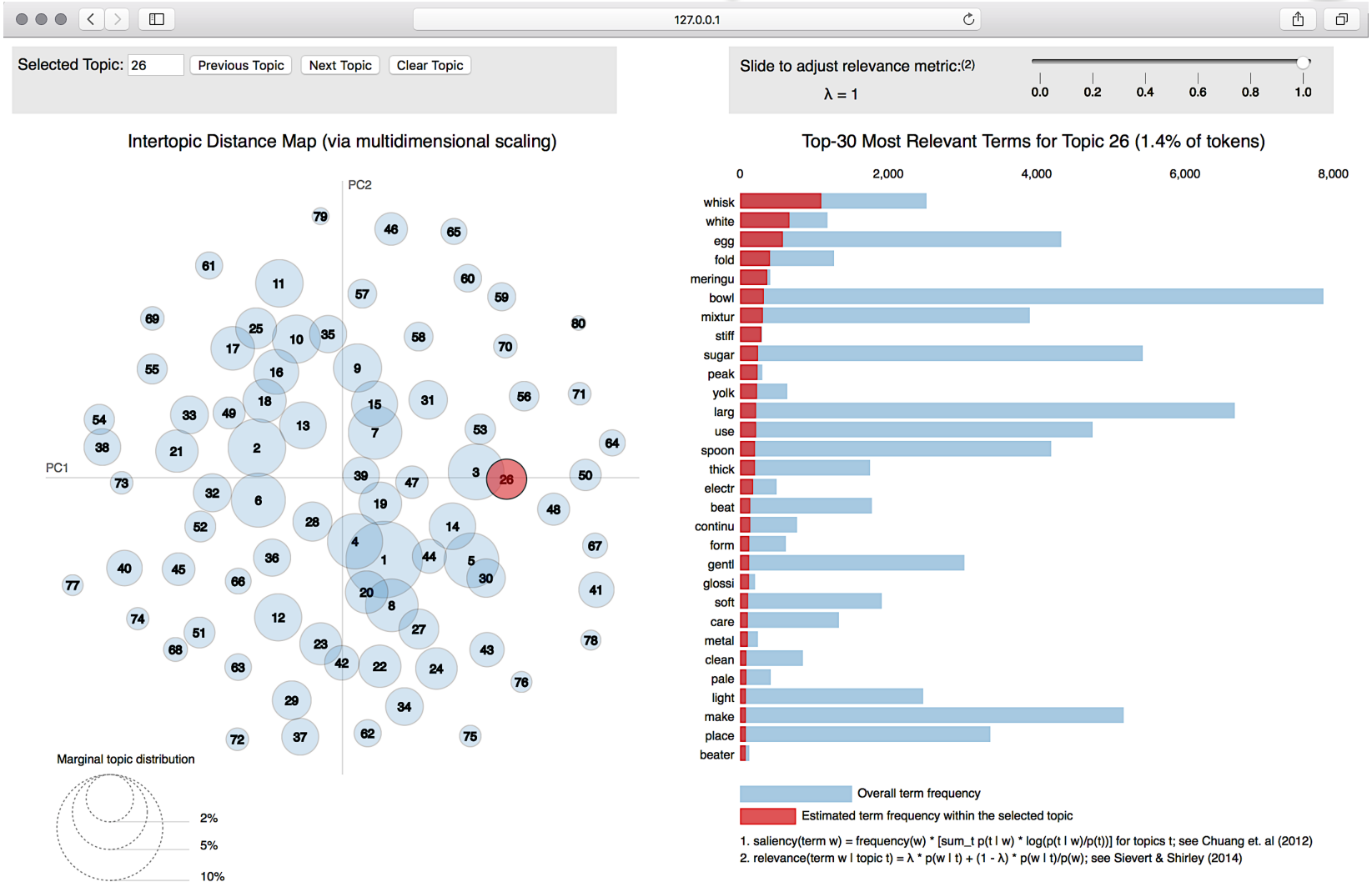
Ingredients topic-modeling



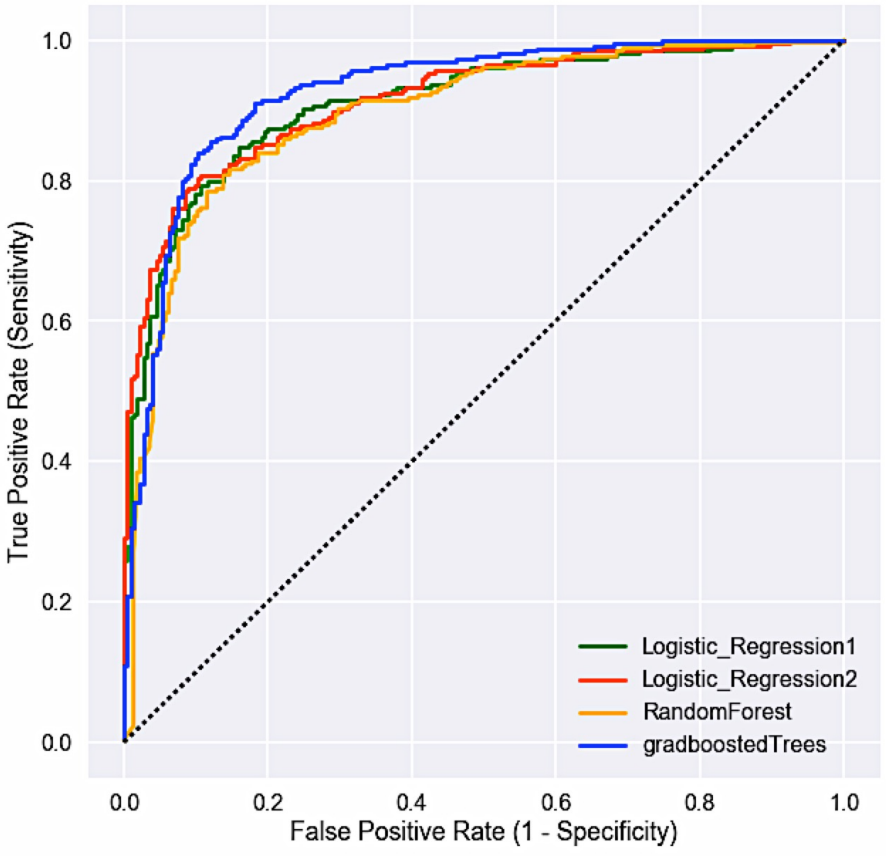
Chocolate-y
Topic 67: sugar flour powder egg butter self-rais bake caster milk cocoa extract plain vanilla dark-chocol ice
Topic 33: cream doubl butter dark-chocol milk sugar whip serv egg coffe liqueur liquid glucos squar disaronno

Chicken
Topic 63: chicken stock thigh onion garlic butter duck liver drumstick sunflow chorizo cornichon
Topic 74: breast chicken boneless skinless oliv blue onion sunflow strip zest flour free-rang

Instructions topic-modeling



Classification outcomes on hold-out data:

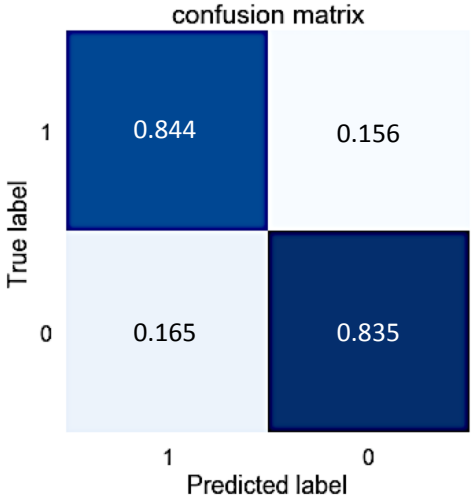


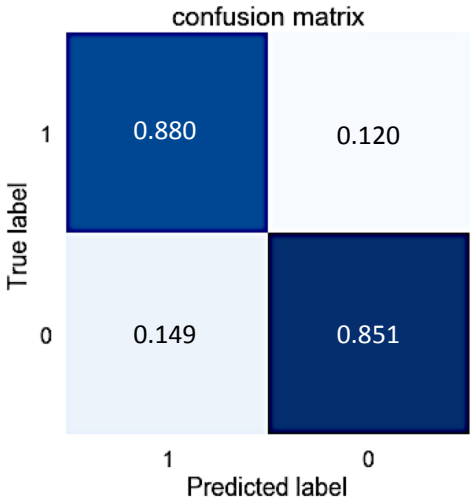
Model: Logistic_Regression1
AUC_test: 0.809
AUC_holdout: 0.840

Model: Logistic_Regression2
AUC_test: 0.816
AUC_holdout: 0.825

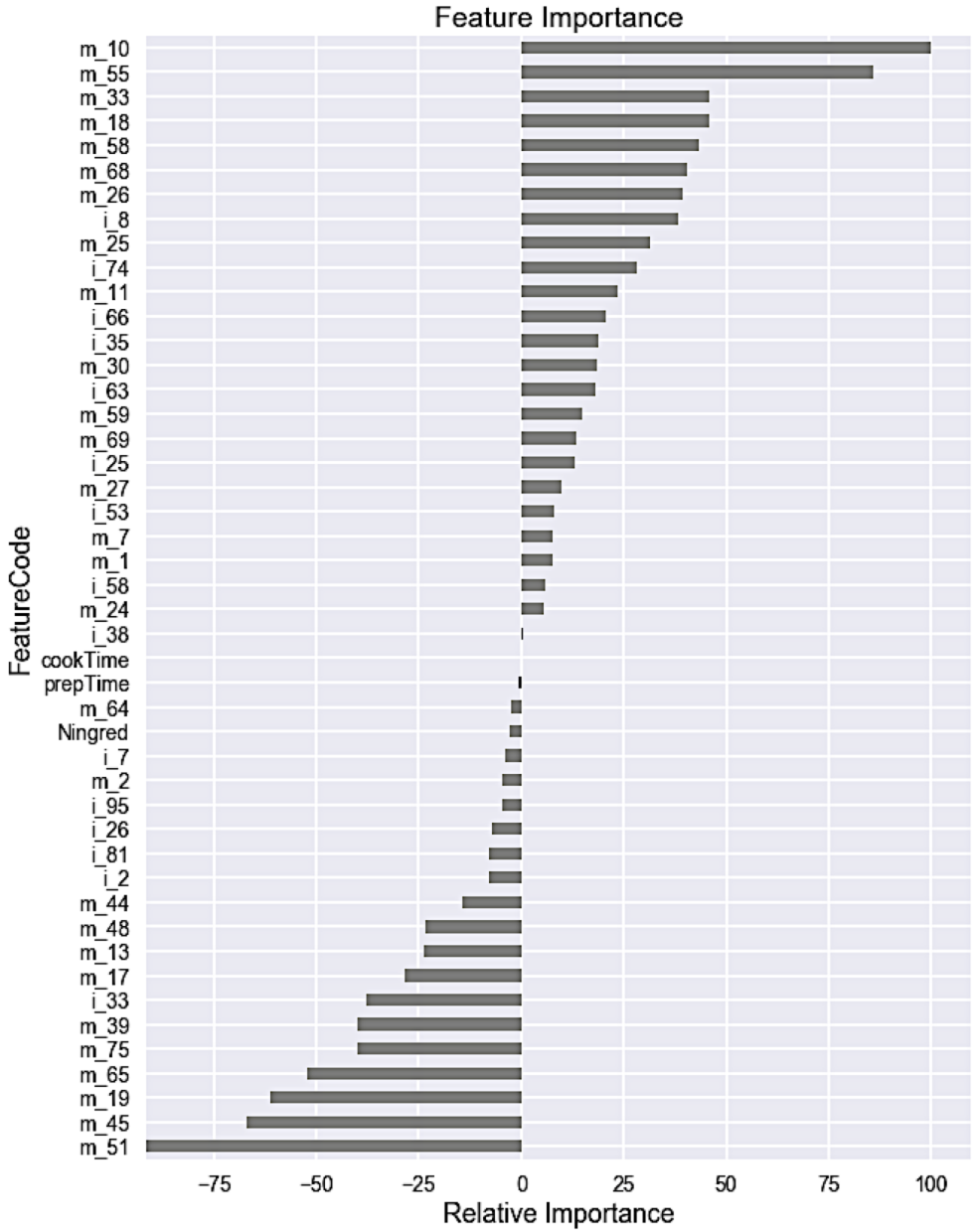
Model: RandomForest
AUC_test: 0.806
AUC_holdout: 0.831

Model: gradboostedTrees
AUC_test: 0.830
AUC_holdout: 0.865





What makes a recipe ~difficult?



 # MTopic 10: soup/stew

MTopic 55: baked oven dish

MTopic 33: pasta

MTopic 18: curry

MTopic 26: casserole dishes

ITopic 8: general baking

ITopic 74: chicken-related

ITopic 66: fingerfood / stew

ITopic 35: basil/Italian -- salad/finger-food

ITopic 33: chocolate/ganache

MTopic 39: pastry/baking/case

MTopic 75: parcel-type method

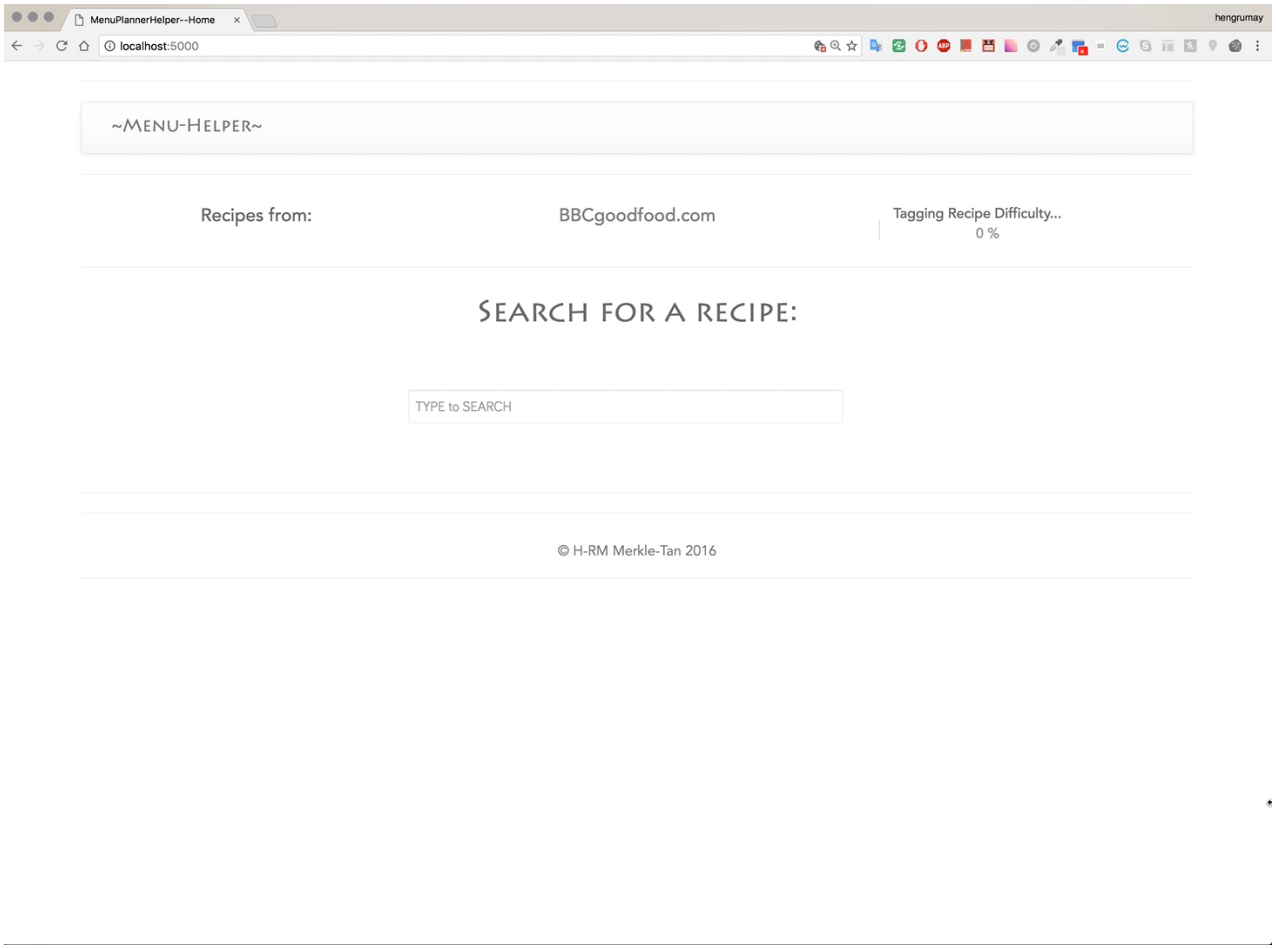
MTopic 65: deep frying

MTopic 19: Roast meat/duck

MTopic 45: custard

 # MTopic 51: meringue

Menu Planner Helper



AWS: http://bit.ly/menuplannerhelper

#Interim Summary

- Recipe Difficulty Tagger: a way to organize/categorize documents
  - Train CRF model for ingredient phrases on BBCgoodfood.com/additional recipes
  - **LDA topic modeling disregards word-order:** maybe useful for recipe instructions
    → LDA2Vec ~= LDA + Word2Vec
- Usage:
  - Tag recipes from other sites and test recipe similarity suggestions
  - Collect users' feedback to assess and update model
  - Personalized 'learning' tool: tailoring your cooking adventure – where the model could be adapted with user's experience
- Apply methodology to other types of documents

With thanks to:

Natural Language
Analyses with NLTK

CRF++: Yet Another CRF toolkit

machine learning in Python

THANK YOU

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