POS tagging probability weighted method for matching the Internet recipe ingredients with food composition data

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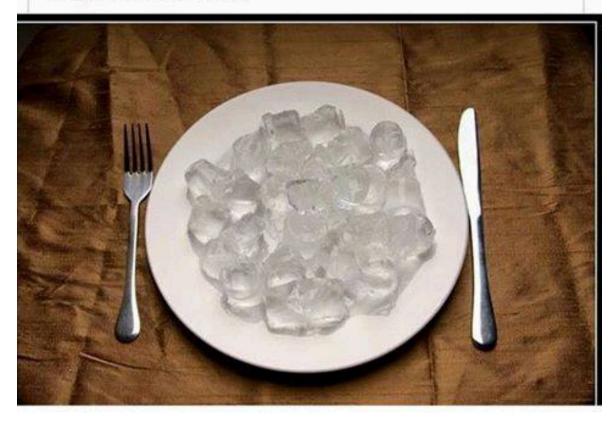
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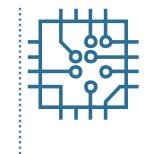
Overview

- Motivation
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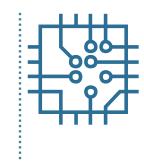
Motivation

Finally settling down to my vegan, gluten free, soy free, antibiotics free, raw, non GMO, organic, fat free, low carb meal!





Introduction



- Food composition databases (FCDBs)
- Internet recipes
- Information retrieval method

Related work



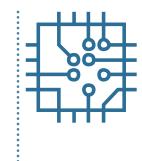
- Matching text concepts to an entry in a knowledge base has been addressed in many ways
- Muller et al. (2012) presented a system that automatically calculates the nutritional content of recipes sourced on Internet
 - 6 human assessors manually evaluate list of ingredients for ambiguous ingredient names
 - 1,515 positively classified instances to witch they added the same number of negatively classified instances
 - features extraction and penalized regression model
 - 91.1% of the recipes they used were matched completely

Problem definition

- People use human language to write the names of the used ingredients
 - "salt iodised", "iodised salt", "salt, idodised"
- Ingredient synonymy problem
- The form of the ingredient and the cooking process

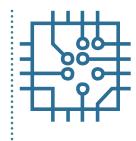




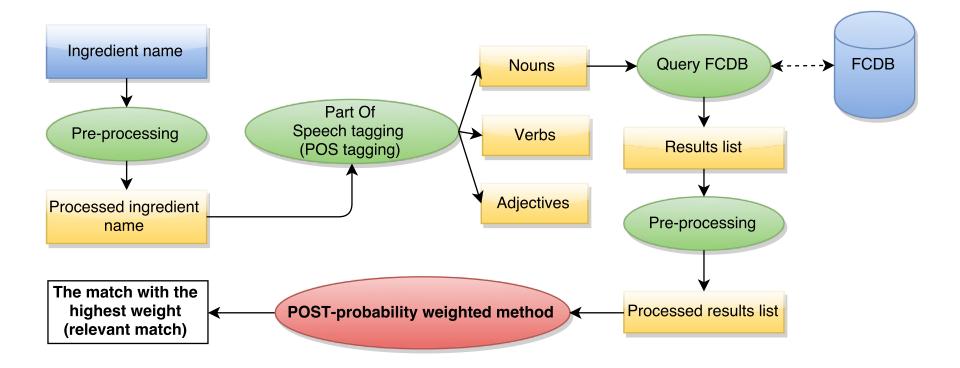


Proposed method (1/2)

- POS tagging (NN*,JJ*,VB*)
- String similarity Jaccard index
- Laplace probability estimate



Proposed method (2/2)

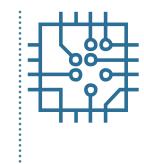


Evaluation and results

- Data collection of 721 recipes written in English ¹
- 1,615 different names of ingredients
- EuroFIR FCDB²
 - food table
 - ENGFDNM
- 44,033 English names of food analyses

¹ <u>http://allrecipes.com/</u>

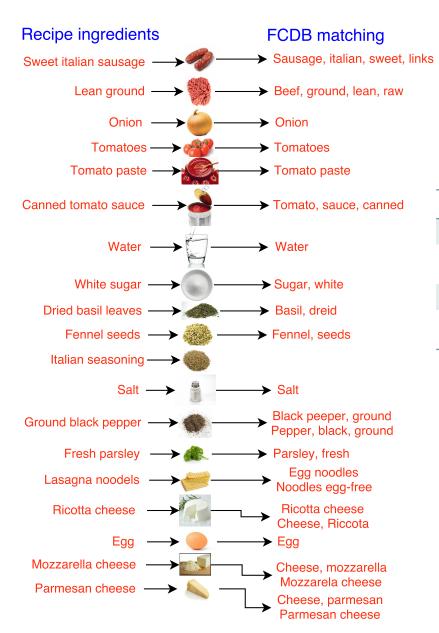
² EuroFIR – non-profit Association under the Belgian law, <u>http://www.eurofir.org/</u>

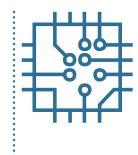


Data pre-processing

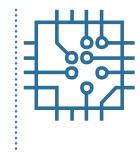
- Remove punctuations
- Convert each name in lower case letters
- Whitespace tokenization
- Lemmatization, only for nouns
- Manually created rules (without skin; skinless), (with salt; salted)

Experiment 1



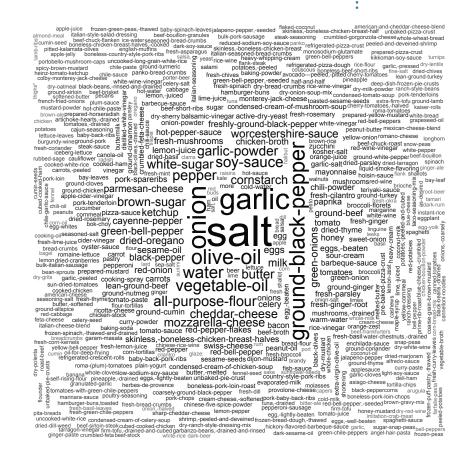


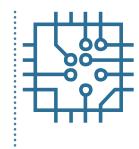
Recipe	FCDB	Code
gibanica	prekmurska gibanica	RECMEM000162
	sojina omaka tamari	
omaka sojina	(iz soje)	16124
pomaranče	pomaranča	P0402
	melona casaba	9183
melona	melona honeydew	9184



Experiment 2 (1/2)

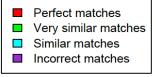
- We divided the matches on 4 groups
- *Perfect*, *Very similar*, *Similar* and *Incorrect* matches
- Perfect 1,210 (74.92%)
- Very similar 273 (16.90 %)
- Similar 78 (4.84%)
- Incorrect 54 (3.34%)





Experiment 2 (2/2)

- Perfect matches
 - (black olives; olives, black)
 - (fresh ginger; ginger, fresh)
- Very similar matches
 - (fresh cilantro; spices, coriander seed (cilantro))
 - (uncooked egg noodles; egg noodles)
- Similar matches
 - (dry penne pasta; pasta, without egg, dry)
- Incorrect matches
 - (angel hair pasta; cake angelfood, commercially prepared)
- Perfect and very similar matches are 91.82% together





Conclusion

- Method for matching recipe ingredients with food composition data
- Can be use to explore what is missing in the FCDBs
- No need of labeled data
- The result can be used for feature selection and then solving classification problems

Quisper Ontology Learning from Personalized Dietary Web Services

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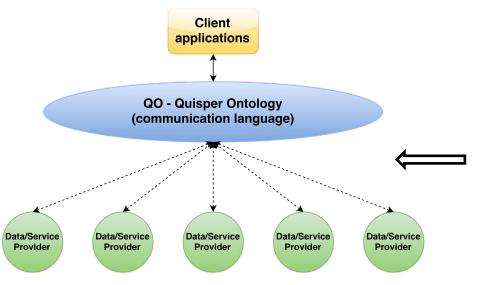


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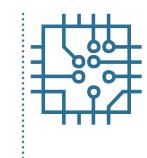


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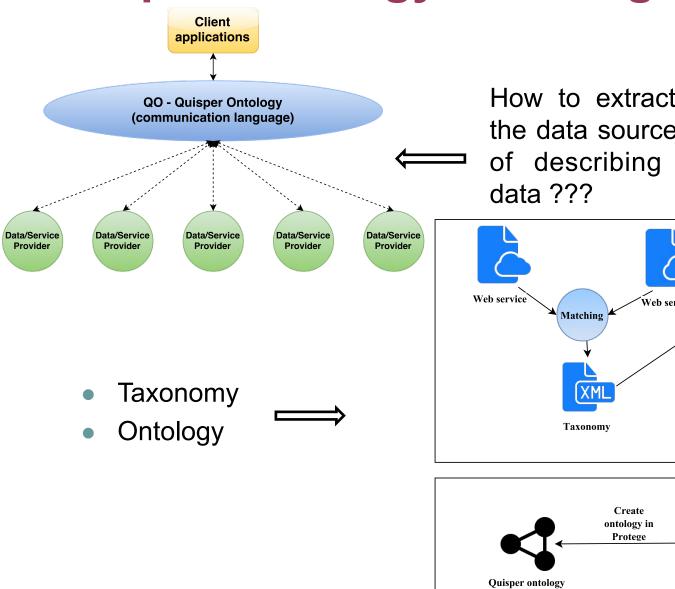
Quisper Ontology Learning



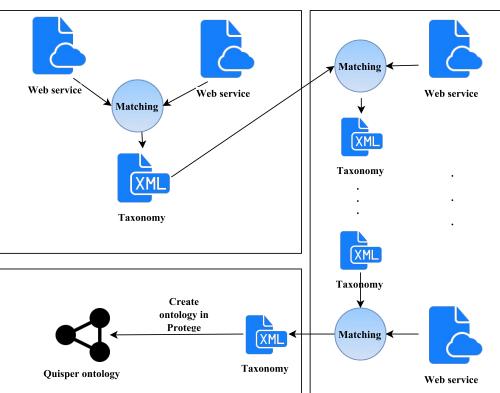
How to extract the knowledge from the data sources using different ways of describing and classifying the data ???



Quisper Ontology Learning

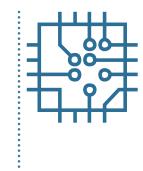


How to extract the knowledge from the data sources using different ways of describing and classifying the data ???

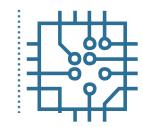


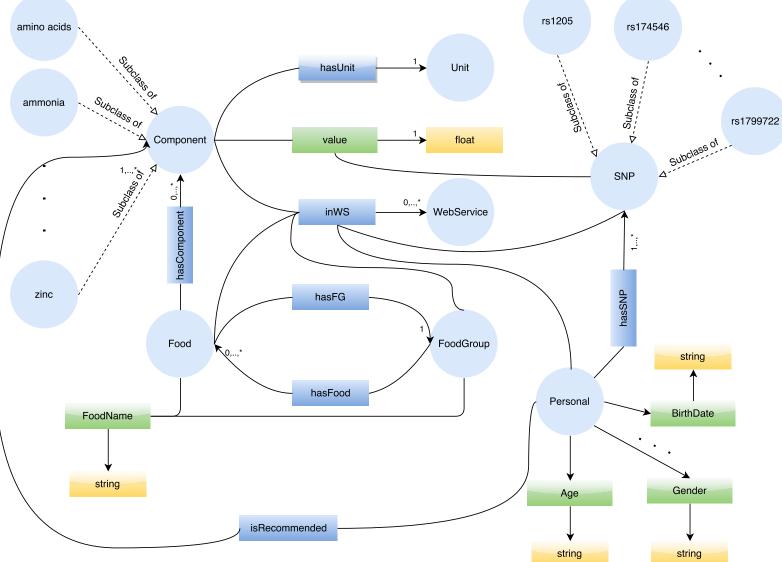
Quisper taxonomy

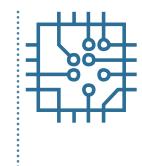
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Quisper ontology







Thank you for your attention!!!

