Automatic Zoom Level Prediction for Informal Location Descriptions

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Talk Outline

Introduction

- Extensive literature on:
  - geographic information systems (= retrieve the set of spatial objects associated with a query, e.g. by geoparsing, and render the results on a map)
  - geographic information retrieval (= ranking documents based on their relevance to a text-based geospatial query)
  - spatial database querying (= query set of spatial objects based on a formal geospatial query)

  but considerably less on generating map-based results for *informal* textual queries

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  but considerably less on generating map-based results for *informal* textual queries
- **Research aim:** automatically predict the appropriate map zoom level for an informal text-based geospatial query

Motivating Example I

Example

corner of como parade east and parkers road, in the library building

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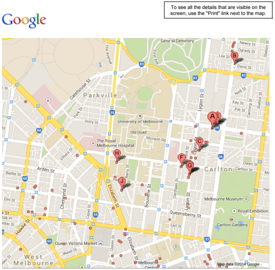
✗

Motivating Example II

Example

waiting for a friend at a cafe in Carlton

✔



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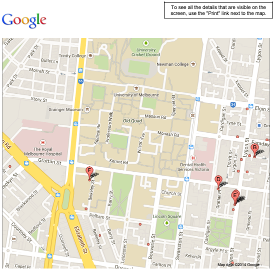

Motivating Example III

Example

at Melbourne Uni

✔

✗

Talk Outline

Dataset

- TellUsWhere = a location-based mobile game where participants were asked to provide a text response to *Tell us where you are* [Winter et al., 2011]
- Total of 1,858 place descriptions, focused primarily around Victoria, Australia
- All geospatial expressions (GEs) in the data manually identified, and annotated for:
  1. zoom level
  2. identifiability
  3. canonical lexicalisation
- Overall document also annotated for zoom level

Zoom Level

- Zoom level is annotated on a scale of 1–7, based on the classification of Richter et al. [2013]:

Zoom level	**Description**
(1) Furniture	Location within a room (e.g. *by my computer*)
(2) Room	Location within a building (*third floor*), or medium-sized vehicle
(3) Building	Location of a building, street no. or building name
(4) Street	Institution, public space or street level, larger than building and/or vaguer boundaries than building.
(5) District	Suburb, rural district or locality, or post code area
(6) City	Town or city level, and metropolitan areas
(7) Country	Everything beyond city level

Identifiability

- The identifiability of each GE is classified according to one of the following classes:
  1. **identifiable non-ambiguous** (uniquely identifying, e.g. *Flemington Road*)
  2. **identifiable ambiguous** (one of a small, bounded set of entities, e.g. *Canning St*, of which there are four in Victoria)
  3. **non-identifiable** (one of a large or unbounded set, e.g. *the park*)
- All annotations relative to the state of Victoria, Australia

Talk Outline

1. Introduction
2. Dataset
3. Zoom Level Prediction Using Gold Standard Data
4. Zoom Level Prediction Using Automatically Predicted Data
5. Conclusions

Zoom Level Prediction Using Gold Standard Data

- First, we attempt to classify the zoom level of a TellUsWhere description, given access to gold-standard annotations of:
  - the GEs in the description
  - the zoom level Z and identifiability class I of each GE

Example (*Predict the zoom level for:*)

$\left[_{Z=3;I=NI}\right.$ *corner* $\left.\right]$ *of* $\left[_{Z=4;I=NA}\right.$ *como parade east* $\left.\right]$ *and* $\left[_{Z=4;I=IA}\right.$ *parkers road* $\left.\right]$, *in* $\left[_{Z=3;I=NI}\right.$ *the library building* $\left.\right]$

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Answer: Z=3

Methodology

- Learner = linear-kernel support vector machine (SVM)
- Features:
  - **zoom**: the zoom level of every GE (Boolean $\times 7$)
  - **unambiguous**: the zoom level of each unambiguous GE (Boolean $\times 7$)
  - **ambiguous**: the zoom level of every ambiguous GE ($\times 7$)
  - **non-identifiable**: the zoom level of every non-identifi-able GE (Boolean $\times 7$)
  - **double**: zoom levels that occur two or more times in GEs within the description (Boolean $\times 7$)
  - **minimum zoom**: the smallest zoom level value for all GEs (Integer^{+} $\times 1$)
- Run experiment based on 10-fold cross-validation; evaluate using classification accuracy and RMSE

Results

Feature set	**RMSE**	**Accuracy**
Most frequent zoom	1.779	0.322
Minimum zoom	1.915	0.593
All	0.932	0.838
−zoom	0.956	0.825
−unambiguous	1.067	0.821
−ambiguous	0.936	0.833
−non-identifiable	0.950	0.832
−double	0.934	0.840
−min. zoom	0.911	0.838
−(min. zoom, double, ambiguous)	**0.901**	**0.841**

Findings

- Classifiers outperform both baselines (weakly and strongly supervised) in all instances
- Best-performing feature set = zoom + unambiguous + non-identifiable (within one zoom level of the correct label, on average)
- Knowledge of both the zoom level and identifiability of each component GE in a location description aids in zoom level prediction

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Zoom Level Prediction Using Automatically Predicted Data

- Highly encouraging results using gold-standard data, but ultimately only useful if we can fully automate the method
- Revised task = classify the zoom level of a TellUsWhere description, given access to gold-standard annotations of:
  - the GEs in the description

Example (*Predict the zoom level for:*)

[*corner* **]** *of* **[** *como parade east* **]** *and* **[** *parkers road* **]**, *in* **[** *the library building* **]**

Predicting the Zoom Level and Identifiability of a GE

- To classify the zoom level and identifiability of a given GE, we:
  - POS tag and full-text chunk the description
  - translate each GE into a feature vector, based on:
    - **following GEs**: the number of GEs within the description that follow the current expression
    - **non-noun count**: the number of words within the GE that are not nouns
    - **capitalised**: are all of the words within the GE capitalised?
    - **preceding preposition**: is there a preposition immediately preceding the GE?
    - **preposition**: does one of ten prepositions precede the GE?
  - train a linear-kernel SVM

Results

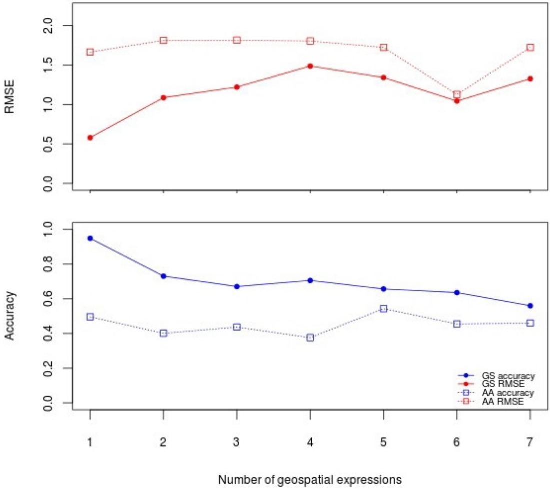
- The GE-level results for the method (based on 10-fold cross-validation) are:

Feature set	Zoom level		Identifiability
	RMSE	Accuracy	Accuracy
All	**1.025**	**0.564**	0.597
−preposition	1.028	0.556	**0.609**

- The description-level results when the GE-level automatic predictions are used are:

Feature set	RMSE	Accuracy
Most frequent zoom	1.779	0.322
Minimum zoom	1.762	0.428
SVM (zoom, unambiguous, non-id)	**1.760**	**0.457**

Breakdown of Results by Number of GEs per Description



Comparison with Google Maps

- To gauge the utility of the method and difficulty of the task, we fed each description (+ *Victoria, Australia*) into Google Maps and evaluated the resulting map based on our zoom level set
- If Google Maps returned no results, we considered the result to be incorrect
- The results are as follows:

Method	**Accuracy**
Gold-standard GE	0.841
Automatic GE analysis	0.457
Google Maps	0.528

Reflections

- Encouraging results with gold-standard zoom and identifiability information; big drop in results when automatically-predicted information is used
- Important to bear in mind that our method doesn't have access to GIS data or any gazetteers
- All results have been based on assumed knowledge of GEs, but note that automatic GE extraction methods perform at $>80\%$ chunk-level F-score [Liu et al., to appear]
- Obvious way forward would be to jointly model the GE- and description-level tasks

Talk Outline

Conclusions

- Framework for predicting the zoom level of informal place descriptions, based on analysis of the zoom level and identifiability of GEs
- Highly encouraging results with access to gold-standard GE information; appreciable drop when GE information was automatically analysed
- When compared with Google Maps, our method much more accurate if given access to gold-standard GE information, but slightly worse than Google Maps without it
- Overall, our experiments point to the potential utility of zoom level and identifiability information of component GEs for zoom level prediction

Acknowledgements

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