SEST-6577
Geographic Information Systems for Security Studies
Lecture 06 (Geocoding)

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What is **geocoding**?

- assignment of geographic code to descriptive locational data

Example:

- input: "Ann Arbor"
- output: (42.281, -83.748)

Figure 1: Find your location!

Geocoder components

- input query (e.g. address)

  ↓
- pre-processing algorithm (tokenization, standardization)

  ↓
- matching algorithm (exact vs. fuzzy, tie-break rule)

  ↓
- reference data (e.g. gazetteer)

  ↓
- output feature (e.g. point, code)

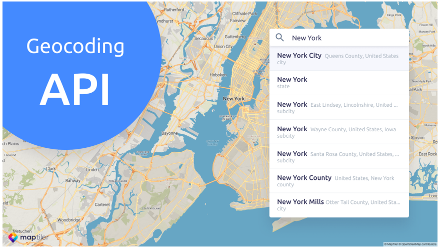
Geocoding
API
New York
New York City Queens County, United States
city
New York
state
New York East Lindsey, Lincolnshire, United ...
subcity
New York Wayne County, United States, Iowa
subcity
New York Santa Rosa County, United States, ...
subcity
New York County United States, New York
county
New York Mills Otter Tail County, United Sta...
city
maptiler
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Figure 2: Input address, output data

Input

Input queries

What can be geocoded?

Descriptive locational data:

1. Postal addresses ("1201 South Main Street, Ann Arbor, MI 48104-3722")
2. Street intersections ("South Main and Stadium, Ann Arbor, MI 48104-3722")
3. Partial addresses ("S. Main St., Ann Arbor, MI")
4. Postal codes ("48104-3722")
5. Named buildings, landmarks ("Michigan Stadium")
6. General place names ("Ann Arbor")
7. Free-form queries ("The Big House")

Figure 3: Hail to the victors

Sources of error in input data

1. Imprecise queries → imprecise output
   (street address vs. county name)
2. Ambiguous queries → multiple matches
   (Springfield, Portland, Alexandria)
3. Too much precision → fewer matches
   (regimental command post at Hill 55)
4. Alt. spellings, typos → false matches
   (Granada, Spain vs. state of Grenada)
5. Place name changes → non-matches
   (Aleksandrovka/Yuzovka/Stalino/Donets'k)
6. Slang, nicknames → non-matches
   ("Paris of the Midwest", "Motown")

How to avoid some of these problems?

- pre-process the text of the input query

Figure 4: Wrong number

Pre-processing algorithm

What is **pre-processing**?

- standardization and normalization of input into a format and syntax compatible with the reference dataset

Why pre-process?

- prevent avoidable geocoding errors
- becomes more important where text is more unstructured, ambiguous
  - easy: "Ann Arbor, MI"
  - hard: "the Michigan city of Ann Arbor"
  - harder: "I met my friend Dallas when we were both college students, living in A2"

Figure 5: Undeliverable address

Common pre-processing tasks

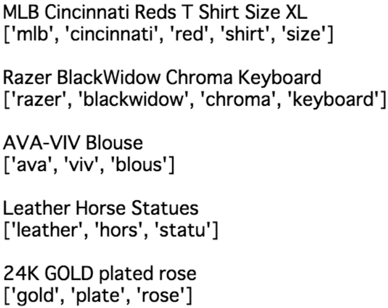
1. Remove HTML tags, control characters
2. Remove non-alphanumeric characters
3. Remove capitalization
4. Remove punctuation
5. Parts-of-speech tagging
6. Lemmatization

Figure 6: Lost in translation

Filtering unnecessary words, text

Why strip capitalization, punctuation, etc?

1. Reconcile address formats
   (Cambridge, MA ≠ Cambridge MA)
2. Raise probability of match
   (Middlesex county → middlesex county)
   (Middlesex County → middlesex county)
3. Avoid computational errors
   (‘#‘, ‘%‘ are special characters in many programming languages)



MLB Cincinnati Reds T Shirt Size XL
['mlb', 'cincinnati', 'red', 'shirt', 'size']

Razer BlackWidow Chroma Keyboard
['razer', 'blackwidow', 'chroma', 'keyboard']

AVA-VIV Blouse
['ava', 'viv', 'blous']

Leather Horse Statues
['leather', 'hors', 'statu']

24K GOLD plated rose
['gold', 'plate', 'rose']

Figure 7: Sentences → Tokens

Parts of speech tagging

Do we care if a word is a noun or a verb?

It depends on the application:

- well-formatted addresses:
  POS unimportant ("Ann Arbor, MI")
- unstructured queries:
  POS more important ("I met my friend Dallas when we were students in A2")
- various POS tagging software available online (`nlp.stanford.edu`)
- some APIs do this automatically

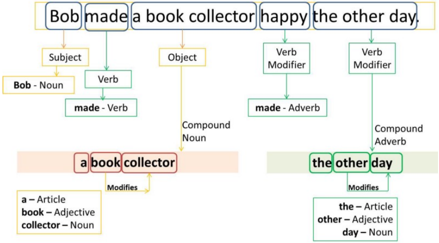


Figure 8: Sentence → POS tags

Lemmatization

relating multiple versions of same word to common, standard term

1. Many-to-one mappings
   - (Ann Arbor, A2, A-squared, the Deuce, Tree Town) → Ann Arbor
   - useful to associate nicknames, historical names with single location
2. One-to-many mappings
   - Dallas → Dallas (TX)
   - Dallas → Dallas (my friend)
   - Jackson → Jackson (MS)
   - Jackson → (Janet) Jackson
   - useful to distinguish places from people
   - requires info about word order, context

Procedure:

- create lookup table for relevant terms
- query table for each occurrence of word
- trade-off: speed vs. accuracy

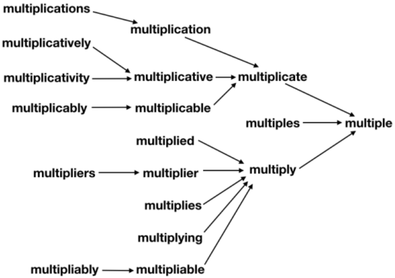


Figure 9: Many-to-one example

Output

Matching algorithm

How to find the best output candidate?

1. Exact vs. fuzzy matching
   - exact: Ann Arbor $\neq$ ann arbor
   - fuzzy: Ann Arbor $\sim$ ann arbor
2. Non-match rule (if zero matches)
   - return N/A?
   - geocode at lower resolution?
   - query additional datasets?
3. Tie-breaking rule (if multiple matches)
   - first match?
   - random match?
   - most precise match?
   - most popular match?

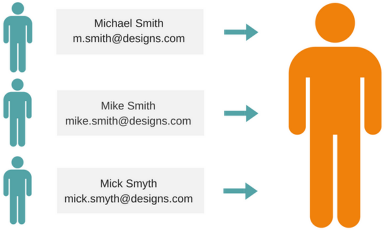


Figure 10: Match-making

Sources of error in matching

1. False positive matches:
   "my friend Dallas" → Dallas, TX
2. False negative matches: "A2" → N/A
3. Multiple matches:
   "Memphis" → Memphis, TN; Memphis, Egypt

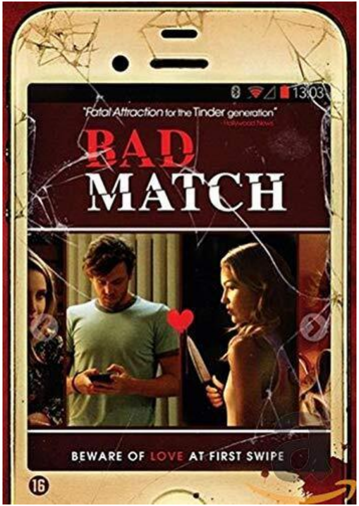

13:03
"Fatal Attraction for the Tinder generation"
BAD
MATCH
BEWARE OF LOVE AT FIRST SWIPE
16

Figure 11: Bad film (probably)

Reference data

What are **reference data**?

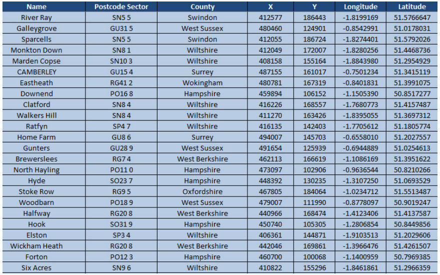
Geographically-coded information used to match input to output

1. Gazetteers
2. TIGER/Lines
3. Crowd-sourced

Figure 12: Like this, but electronic

Gazetteer data

- dictionary of standard and alternate spellings of place names, and their geographic locations
  (e.g. NGA GEOnet Names)



Name	Postcode Sector	County	X	Y	Longitude	Latitude
River Ray	SN5 5	Swindon	412577	186443	-1.8199169	51.5766647
Galleygrove	GU31 5	West Sussex	480460	124901	-0.8542991	51.0178031
Sparcells	SN5 5	Swindon	412055	186724	-1.8274401	51.5792026
Monkton Down	SN8 1	Wiltshire	412049	172007	-1.8280256	51.4468736
Marden Copse	SN10 3	Wiltshire	408158	155164	-1.8843980	51.2954929
CAMBERLEY	GU15 4	Surrey	487155	161017	-0.7501234	51.3415119
Eastheath	RG41 2	Wokingham	480781	167319	-0.8401831	51.3991075
Downend	PO16 8	Hampshire	459894	106152	-1.1505390	50.8517277
Clatford	SN8 4	Wiltshire	416226	168557	-1.7680773	51.4157487
Walkers Hill	SN8 4	Wiltshire	411270	163426	-1.8395055	51.3697312
Ratfyn	SP4 7	Wiltshire	416135	142403	-1.7705612	51.1805774
Home Farm	GU8 6	Surrey	494007	145703	-0.6558010	51.2027557
Gunters	GU28 9	West Sussex	491654	125939	-0.6944889	51.0254613
Brewerslees	RG7 4	West Berkshire	462113	166619	-1.1086169	51.3951622
North Hayling	PO11 0	Hampshire	473097	102906	-0.9636544	50.8210266
Hyde	SO23 7	Hampshire	448392	130235	-1.3107250	51.0693529
Stoke Row	RG9 5	Oxfordshire	467805	184064	-1.0234712	51.5513487
Woodbarn	PO18 9	West Sussex	479007	111990	-0.8778097	50.9019247
Halfway	RG20 8	West Berkshire	440966	168474	-1.4123406	51.4137587
Hook	SO31 9	Hampshire	450740	105305	-1.2806854	50.8449856
Elston	SP3 4	Wiltshire	406361	144871	-1.9103513	51.2029606
Wickham Heath	RG20 8	West Berkshire	442046	169861	-1.3966476	51.4261507
Forton	PO12 3	Hampshire	460700	100068	-1.1400959	50.7969385
Six Acres	SN9 6	Wiltshire	410822	155296	-1.8461861	51.2966359

Figure 13: Example gazetteer data

Topologically Integrated Geographic Encoding and Referencing (TIGER/Line)

- U.S. Census Bureau's digital database for finding locations along roads

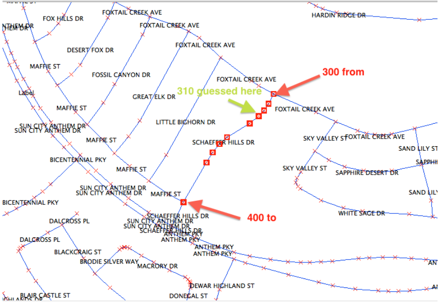


Figure 14: Example TIGER/Line

Crowd-sourced data

- user-generated location data from surveys, GPS devices, free sources (e.g. OpenStreetMap Nominatum)

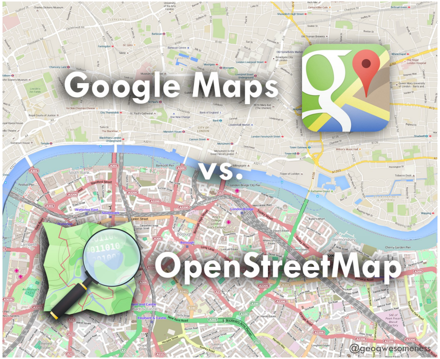


Figure 15: OSM is free, Google isn't

Sources of error in reference data

- data quality can be region-specific (e.g. Google vs. Yandex)
- less precise, sparser data in rural areas and developing countries
- some datasets not frequently updated
- different datasets use different standard name spellings

Figure 16: Re-routing

What is the **output**?

Any geographically-referenced information:

1. Point coordinates
   (longitude, latitude)
2. Line features
   (TIGER line segment)
3. Polygon features
   (parcel of land, census block, census tract, municipality, district, region, country)

Figure 17: Location found!

Sources of error in output

1. Point locations for areal references
   - geographic centroid?
   - capital city?
   - population-weighted centroid?
2. Linear interpolation on TIGER/Line shapefiles

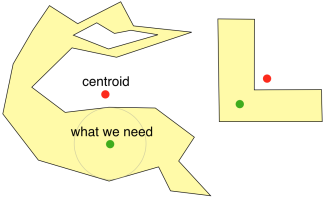


Figure 18: Wrong centroid

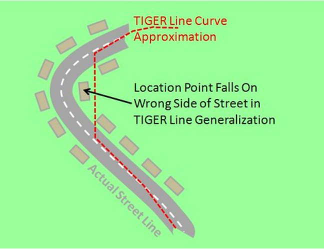

TIGER Line Curve Approximation
Location Point Falls On Wrong Side of Street in TIGER Line Generalization
Actual Street Line

Figure 19: Wrong line