spatial auto-correlation (pysal)

adam.okulicz.kozaryn@gmail.com

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outline

intuition

spatial weights

using spatial weights: spatial auto-correlation

TODO: K-means, medians etc

outline

correlation and spatial auto-correlation

- everyone heard of correlation, right? what is it? examples?
- many things correlate positively; people in space, too
- obese with obese; smokers with smokers, etc
- people you hang out with are like you

  `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3343772/pdf/nihms-216230.pdf` p11 vis
  - `https://www.google.com/search?q=christakis+fowler+obesity`
- `http://www.thebigsort.com/maps.php`
- hi-crime neighborhoods next to hi-crime neighborhoods
- even poor states next to poor states (Miss, Alab, etc)
- poor countries cluster together, too: Africa, Lat Am, etc

the first law of geography (Waldo Tobler)

- "Everything is related to everything else,
- but near things are more related than distant things"
- almost always true!
  - do you see this in your research?

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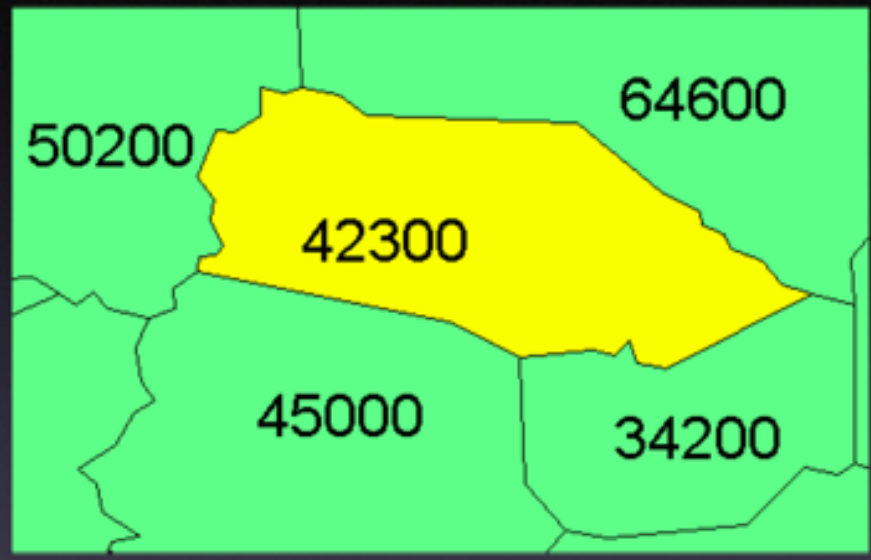
the first step

- the first step before producing spatial auto-corr
- is to produce spatial weights
- or spatially lag a variable

we will spatially lag a variable

- it's like time lagging a variable draw a var and its lag
  - time lagging is useful in exploring temporal precedence
  - eg you may want to know what is the corr/effect of unemployment last year on this year's poverty
- spatially lagged var: want to know the relationship of
- a place to its neighbors
- spatially lagged variable is just
  - an average of values for its neighbors

Spatial Lag Example



Average Neighbor Land Values

1/4x50200 + 1/4x45000 + 1/4x34200 + 1/4x64600

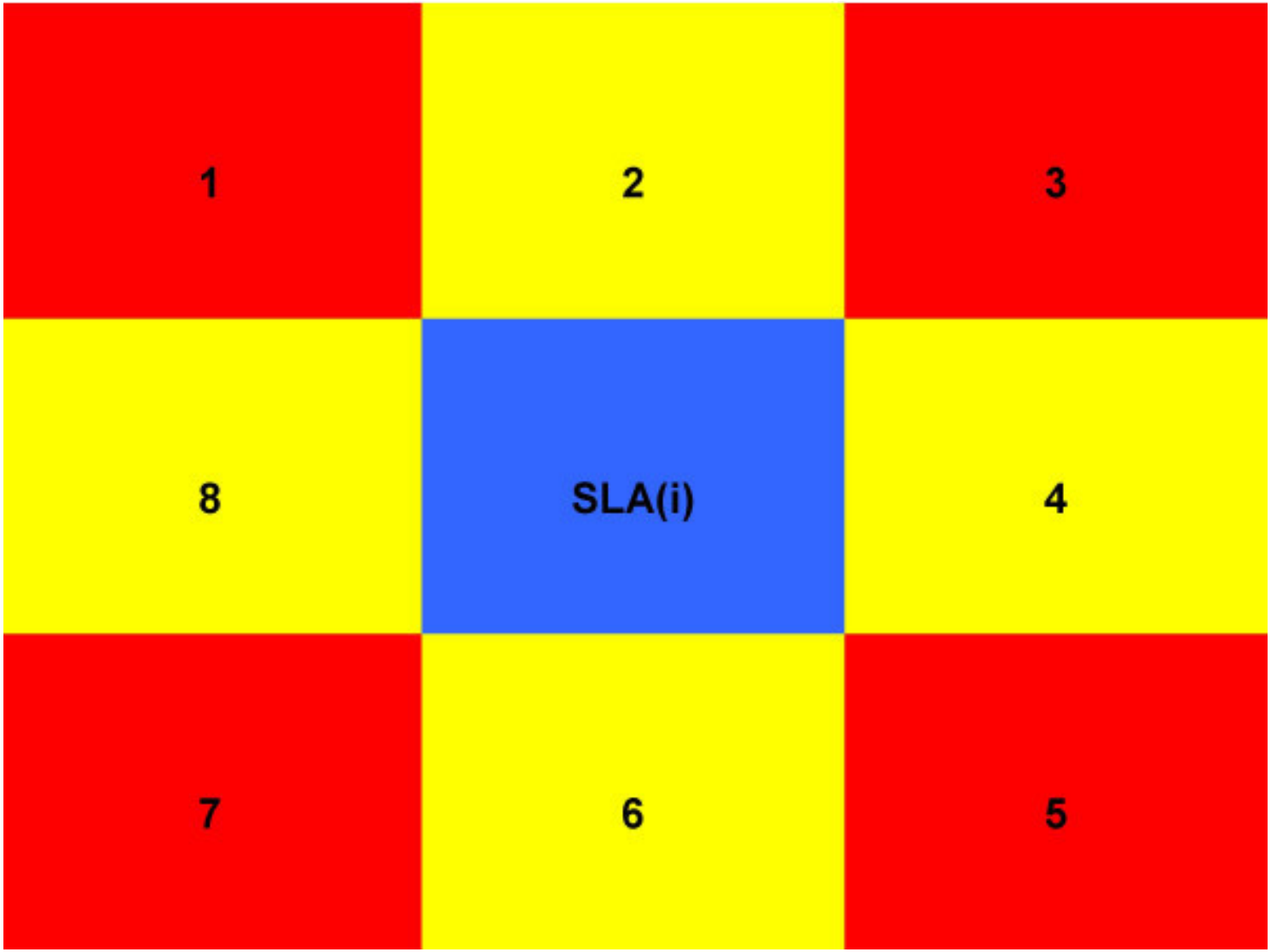
2 ways

- contiguity based (we'll just do these):
  - neighbor of place A touches on place A
- distance based: neighbor of place A is within some distance of place A

2 types of contiguity weights

- usually just pick queen contiguity–neighbor is any place that neighbors our place
  - at least must share a vertex, say North, North-East, etc
- can do rook: must share a border, not just vertex
  - so *not* North-East

rook v queen



- Rook: only 2,4,6, 8; Queen: all (i.e. 1-8)

order of contiguity

- can be higher orders: neighbors of my neighbors are my neighbors
- we'll just do 1st order

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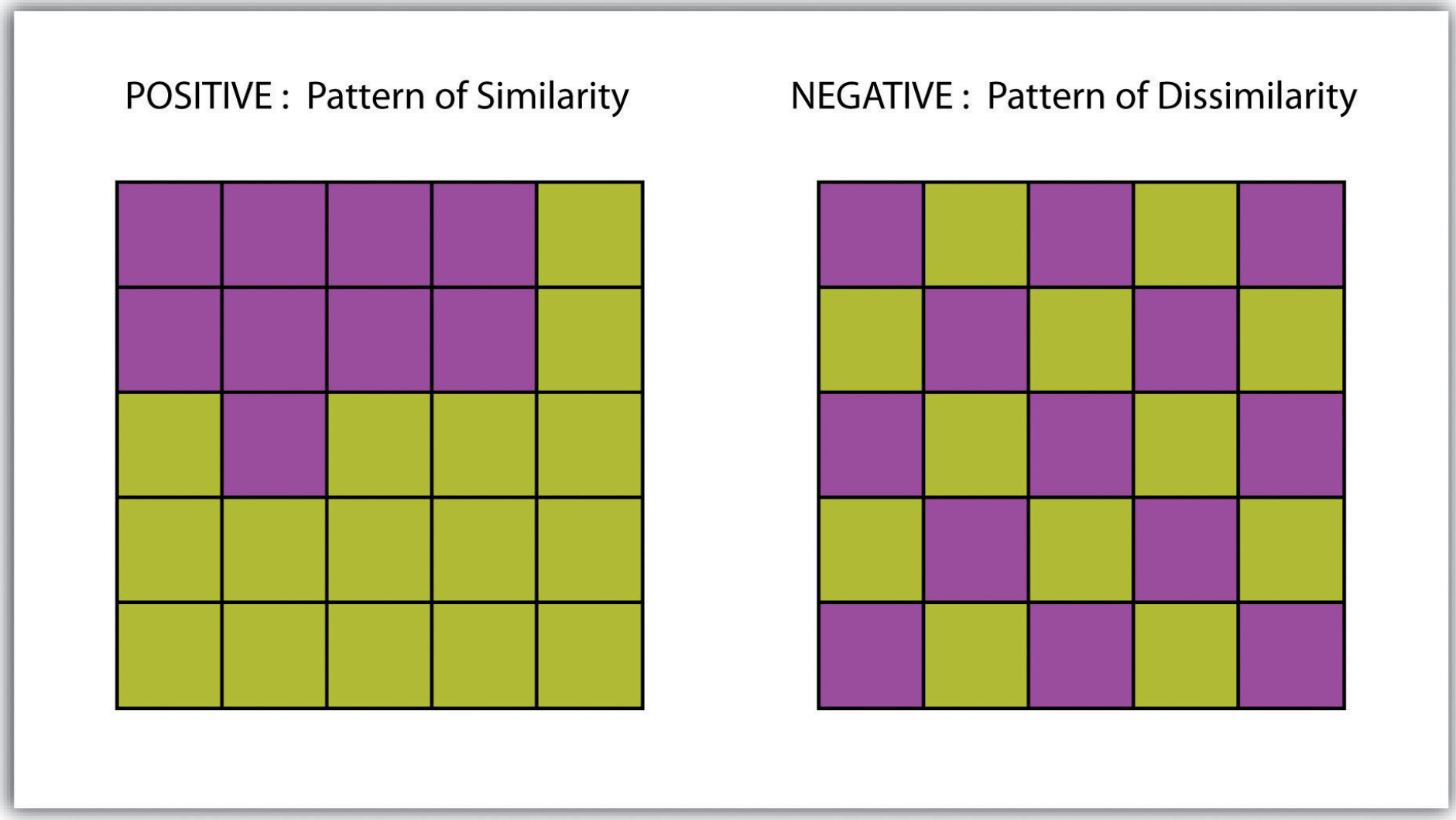
positive v negative spatial autocorrelation

- note: autocorrelation
- correlate values of a var with values of the same var
- corr the variable with its spatial lag (avg for neighbors)
- positive if similar values next to each other
- negative if dissimilar values next to each other
  - can already see it in plain thematic maps!

pos and neg

- 
POSITIVE : Pattern of Similarity
NEGATIVE : Pattern of Dissimilarity

negative correlation is even more interesting

- uncommon: more interesting
- if a dog bites a man its no news,
  if a man bites dog, that's news
- eg sometimes you will see rich area in the middle of
  poverty

application: my paper about happiness in Europe

- `https://theaok.github.io/docs/gesis3.pdf`
  - see histogram and maps
- positive spatial autocorrelation
- clusters of happy and unhappy provinces
  - and they span across country boundaries
  - it is interesting to identify them and formally test it

just a thematic map

- already see spatial auto-correlation in thematic maps
- just have a close look, and think about it, discuss in ps
- still, spaital auto-corr (Moran's I) puts a number on it
  - and LISA (local spatial auto-corr often finds overlooked patterns)

Moran's I

- it's a basic spatial statistic
- just like regular correlation (from -1 to 1) see Moran's I scatter in `https://theaok.github.io/docs/gesis3.pdf`

so what?

- Moran's I and LISA help make sense of thematic maps
  - they identify patterns, clusters, outliers
  - very useful! eg is poverty concentrated?
  - can already see from thematic maps but Moran's I and LISA add precision beyond eye-balling choloropleths
- likewise, histograms make sense of the distribution better than thematic maps
- always: don't forget about interpretation
  - (don't ever show anything that you don't interpret)

so what?

- and it does matter where in the cluster one is located
- eg being poor in the middle of poverty may be better
- than being poor next to rich

we're doing space, but think about time, too

- not only focus on location of greatest poverty, crime etc
- over-time changes matter, too
- greatest or smallest increase
- largest change from well-established trend
- trend
- etc
- show 2 maps, say 1950 map next to 2000 map
- or calculate new var (2000-1950)/1950

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DEFINITELY DO NEXT TIME