Modeling Population Structure and Language Change in the St. Louis Corridor

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NWAV 46, November 6, 2017 University of Wisconsin

Outline

- History of the Northern Cities Shift in the St. Louis Corridor
- Frameworks for Population-Level Change
- Modeling Change in the Corridor

Slides Available Here: ling.upenn.edu/~jkodner₂

History of the NCS in the St. Louis Corridor



- Dialect region within Midlands between Chicago and St. Louis
- And Inland North "island"



- Dialect region within Midlands between Chicago and St. Louis
- And Inland North "island"
- The Northern Cities Shift has advanced and retreated there



Shape of the Corridor

• Follows Old Route 66 from outside Chicago to St. Louis



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- Route 66 passed through Springfield and Bloomington,



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- Follows Old Route 66 from outside Chicago to St. Louis
- Route 66 passed through Springfield and Bloomington,
- And near Decatur, Peoria, Champaign,
- And many small towns



Route 66

- Construction began in 1926
- Replaced a series of unpaved roads and canals
- Connected the main streets of towns along its path



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- Superseded by I-55 in 1957
- Decommissioned in 1985



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 NCS entered the Corridor via Route 66 during the Great Depression (Only period with net migration

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NCS in the Corridor

- NCS entered the Corridor via Route 66 during the Great Depression (Only period with net migration out of Chicago into smaller cities)
- NCS observed first in "on-route" cities, then in "off-route" cities
- Has since largely receded



- Path of change is different On-Route and Off-Route
 - NCS peaks first On-Route
 - NCS peaks higher On-Route
 - Peaks Off-Route about one generation later



Friedman 2014

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 - NCS peaks first On-Route
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 - Peaks Off-Route about one generation later
- Similar path for all variables

On-Route

Off-Route



Friedman 2014

The Hypothesis (Friedman 2014)

- Adult speakers imported the NCS to the Corridor in the 1930s
- It was transmitted to learners in On-Route communities
- These diffused it to nearby towns Off-Route
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- Historical data is highly suggestive of this course of events
- Is there a way to test it without a time machine?
- Yes! We can simulate it

Modeling Population-Level Change



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It would be nice to test cause and effect directly.

Simulation provides that outlet.

A useful tool in computational biology, epidemiology, ... geology, etc.

- **1. Concrete Frameworks**
- 2. Network Frameworks
- 3. Algebraic Frameworks

1. Concrete Frameworks

- Individual agents on a grid moving randomly and interacting (e.g., Harrison et al. 2002, Satterfield 2001, Schulze et al. 2008, Stanford & Kenny 2013)
- + Gradient interaction probability for free
- + Diffusion is straightforward
- Not a lot of control over the network
- Thousands of degrees of freedom -> should run many many times -> slow
- Unclear how to include a learning model

- **1. Concrete Frameworks**
- 2. Network Frameworks
 - Speakers are nodes in a graph, edges are possibility of interaction (e.g., Baxter et al. 2006, Baxter et al. 2009, Blythe & Croft 2012, Fagyal et al. 2010, Minett & Wang 2008, Kauhanen 2016)
 - + Much more control over network structure
 - + Easy to model concepts from the sociolinguistic lit. (e.g., strong/weak)
 - Nodes only interact with immediate neighbors -> slow and less realistic?
 - Practically implemented as random interactions between neighbors -> same problem as #1

- **1. Concrete Frameworks**
- 2. Network Frameworks
- 3. Algebraic Frameworks
 - Expected outcome of all interactions is calculated directly (e.g., Abrams & Stroganz 2003, Baxter et al. 2006, Minett & Wang 2008, Niyogi & Berwick 1997)
 - + Less reliance on random processes -> faster and more direct
 - + Clear how to insert learning models into the framework
 - No network structure! Always implemented over perfectly mixed populations

What We Use

• An algebraic model operating on network graphs

What We Use

- An algebraic model operating on network graphs
 - No random process in the core algorithm
 - Fast and efficient
 - Models language change in social structures

The best of both worlds!

Vocabulary for this Talk

Different research traditions, Different vocabularies

L: That which is transmitted

Language ≈ Variable ≈ *Lect ≈ E-Language

G: That which generates/describes/distinguishes L That which is learned/influenced by L Grammar ≈ Variant ≈ I-Language

The Model

Language change is a two step loop

- 1. Propagation: calculate how L spread
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If this were a linear chain,

$$L_0 \rightarrow G_1 \rightarrow L_1 \rightarrow G_2 \rightarrow L_2 \rightarrow \dots \rightarrow L_n \rightarrow G_{n+1} \rightarrow \dots$$

Mathematical Description

[REDACTED]

Propagation

Network Structure

• Nodes

- How many people are there?
- How are people clustered? Socially or geographically?
- Do people migrate?



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- Are interactions equal? By likelihood, frequency, or social valuation?
- Can the mode of interaction change over time?



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Replacement

- Are we modeling large scale (generations) or small scale (older/younger siblings) change?
- \circ Does the network grow or shrink?



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Modeling Change in the Corridor



Modelling the Corridor: Network Structure

Community Types:

- Midlands (1; "background")
- Chicago (1)
- **On-Route** (19)
- Off-Route (19)



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Community Types:

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- **On-Route** (19)
- Off-Route (19)

Connections:

- Midlands to all On-Route and Off-Route
- Chicago to all On-Route
- On-Route to two adjacent On-Route
- On-Route to one adjacent Off-Route
- Off-Route to one adjacent Off-Route



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 - Movement Off-Route
 - Strength of connections between On-Route and Off-Route
 - Strength of connections between On/Off-Route and Chicago/Midlands
 - Advantage of NCS
 - **Etc.**
- And the results would be less meaningful

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Still important! Just not the focus of the current study...

- Vary a single parameter: Direction of movement to On-Route communities
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Stage 1 - 5 iterations

No migration (speaker interaction only)

Stage 2 - 20 iterations

2% migration from Chicago to On-Route "Great Depression"

Stage 3 - 75 iterations

2% migration from Midlands to On-Route "Post-Depression"

Modelling the Corridor: The Variable

- Treating the NCS as a single binary variable subject to competing grammars
- Community Variable Distributions:
 - Chicago fixed at 100% NCS+
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- Tested as neutral, slightly advantaged, and heavily advantaged change

Two-Compartment Systems

 A type of dynamical system arising in in electrical engineering, medicine, chemistry, ecology...



Two-Compartment Systems

- A type of dynamical system arising in in electrical engineering, medicine, chemistry, ecology...and linguistics!
- Here, On-Route and Off-Route are the compartments
- And the time for variable propagation is the delay



Results: Neutral Change

• A classic two-compartment pattern arises



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- A classic two-compartment pattern arises
- NCS peaks higher and earlier On-Route than Off-Route



Results: Neutral Change

- A classic two-compartment pattern arises
- NCS peaks higher and earlier On-Route than Off-Route
- NCS continues to increase
 Off-Route even after On-Route
 population movements are
 reversed



Results: Advantaged Change

- Advantaged change resists being "tamped down" Off-Route
 - NCS recedes given a slight advantage
 - NCS advances given a heavy advantage





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- Exists some threshold above which indirect action via On-Route is insufficient





Can Great Depression migrations account for the general path of change?

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Was it the only factor?



Can Great Depression migrations account for the general path of change? YES!

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Was it the only factor? NO...



Discrepancies

Gap between the peaks

• Due to our (overly) simple schematized network



Discrepancies

Gap between the peaks

- Due to our (overly) simple schematized network
- **Persistent NCS Off-Route**
 - Could force it into the model...
 - But pattern strongly suggestive of social factors



Questions?

Code Available Here:

github.com/jkodner05/NetworksAndLangChange

Slides Available Here: ling.upenn.edu/~jkodner

Special Thanks: Chris Cerezo Falco Charles Yang ARO NDSEG

Extra slides: Math

Special Acknowledgement: Christopher Cerezo Falco (UPenn)

Network Structure

- *n* x *n* adjacency matrix A
 - Value at a_{ii} indicates interaction from *j* to *i*
 - Must be column stochastic (columns sum to 1)
 - Undirected if for all $i, j, a_{ii} = a_{ii}$ (result row stochastic)

- **A** *n* x *n* adjacency matrix
- H n x c community-membership
- B c x g distr. of grammars in comms
- P c x g distr. of grammars in inputs
- α jump parameter

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- *n* x c indicator matrix H
 - Values are 0 or 1
 - Identifies individuals as members of communities
 - H = I (n=c) if community membership is irrelevant

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 - \circ Value at b_{ii} indicates proportion of speaker j's outputs generated by grammar i
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- Scalar "jump" parameter α
 - Between 0 and 1

• Probability of interaction from *i* to *j* equals the probability of travelling from *i* to *j* along some path

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- Edge weight is segment probability between adjacent *i* and *j*
- Probability of taking another jump decays according to geometric distribution
- Interaction likelihood decreases with social distance

Grammar Distribution Function

$$\mathbf{P}_{t+1} = \mathbf{B}^{\top} \boldsymbol{\alpha} \left(\mathbf{I} - (1 - \boldsymbol{\alpha}) \mathbf{A} \right)^{-1} \mathbf{H} (\mathbf{H}^{\top} \mathbf{H})^{-1}$$

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- Single calculation for the entire population...FAST
- Requires an *n* x *n* matrix inversions...MEMORY INTENSIVE

Tracking Communities

- If fine-grain detail is unnecessary, tracking community averages provides substantial computational speedup when *c* << *n*
- If each community is internally uniform, n x n A admits a c x c equitable-partition A^π
- Yielding a more efficient but equivalent update formula for P

$$\mathbf{A}^{\boldsymbol{\pi}} = (\mathbf{H}^{\top}\mathbf{H})^{-1}\mathbf{H}^{\top}\mathbf{A}\mathbf{H}$$
$$\mathbf{P}_{t+1} = \boldsymbol{\alpha}\mathbf{B}^{\top}\mathbf{H}(\mathbf{I} - (1 - \boldsymbol{\alpha})\mathbf{A}^{\boldsymbol{\pi}})^{-1}(\mathbf{H}^{\top}\mathbf{H})^{-1}$$

Anecdotally, I can run n = 20,000 nets on my laptop with A^{TT} about as fast as n = 2,000 net with A

Tracking Individuals

If c = n, then H is n x n, and the full descriptive detail of the model is available,
 H becomes the identity matrix, and the formula for P can be simplified

$$\mathbf{P}_{t+1} = \mathbf{B}^{\top} \boldsymbol{\alpha} \left(\mathbf{I} - (1 - \boldsymbol{\alpha}) \mathbf{A} \right)^{-1}$$

Transmission

- Dependent on the learning model
- Our implementation is modular, so many learning models can be slotted in
 - e.g., trigger-based learner (Gibson & Wexler 1994)
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- Our implementation is modular, so many learning models can be slotted in
 - e.g., trigger-based learner (Gibson & Wexler 1994)
 - Variational learner (Yang 2000)
- Let L be the distribution of grammars internalized by a learner who heard P
 - L is a matrix consisting of g vectors $l_1, l_2, ..., l_g$
- Define *g* transition matrices $T_1, T_2, ..., T_g$, one for each potential target grammar

$$\mathbf{I}_i = \text{dominant eigenvector of } \sum_{j=1}^g \mathbf{P}_{t+1;j,i} \mathbf{T}_j$$

Transmission and Grammatical Advantage

- If L = P, learners internalize variants at the rate they hear them
 - This yields neutral change
- Otherwise, learners choose variants in a way that biases some over others
 - Some variants have an advantage over others
 - This yields S-curve change in perfectly mixed populations

- Let there be two languages L₁ and L₂, the extensions of g₁ and g₂, produced with probabilities P₁ and P₂.
- $\mathbf{a} = \mathbf{P}_1[\mathbf{L}_1 \text{ union } \mathbf{L}_2]$ $\mathbf{1} \mathbf{a} = \mathbf{P}_1[\mathbf{L}_1 \setminus \mathbf{L}_2]$
- $b = P_2[L_1 \text{ union } L_2]$ $1 b = P_2[L_2 \setminus L_1]$

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- $a = P_1[L_1 \text{ union } L_2]$ $1 a = P_1[L_1 \setminus L_2]$
- $\mathbf{b} = \mathbf{P}_2[\mathbf{L}_1 \text{ union } \mathbf{L}_2]$ $\mathbf{1} \mathbf{b} = \mathbf{P}_2[\mathbf{L}_2 \setminus \mathbf{L}_1]$
- Let T₁ and T₂ be transition matrices assuming g₁ and g₂ are the target grammars respectively
- $T_1 = [1 \ 0 ; 1-a \ a] \quad T_2 = [b \ 1-b ; 0 \ 1]$

- T1 =[1 0] [1-a a]
- T2 =[b 1-b] [0 1]

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- If the target grammar is g1, then in the limit...
 - Learners who initially hypothesize g1 will always remain in g1
 - Learners who initially hypothesize
 g2 will remain at g2 with
 probability a
 - Or switch to g1 with probability
 1-a