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EVOLAEMP
Language Evolution:
The Empirical Turn

Causal Inference of Evolutionary Networks

Phylogenetic Methods in Historical Linguistics

Tübingen, March 30, 2017

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This research has been supported by the ERC Advanced Grant 324246 EVOLAEMP.

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Introduction: General Idea

General ideas behind my talk:

- current evolutionary network inference methods do not scale well, or are not general enough
- we can treat **languages as information-theoretic variables**, and the cognate sets employed for each concept as samples
- cognacy overlaps define information geometry over languages
- vanishing conditional mutual information can be used to test for **conditional independence between languages**
- principles of causal inference sometimes allow us to infer that one language “causes” another
- directionality of causal signal between languages can be interpreted as the **dominant direction of lexical flow**

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Phylogenetic Lexical Flow Inference

A map of the linguistic history of a region should include

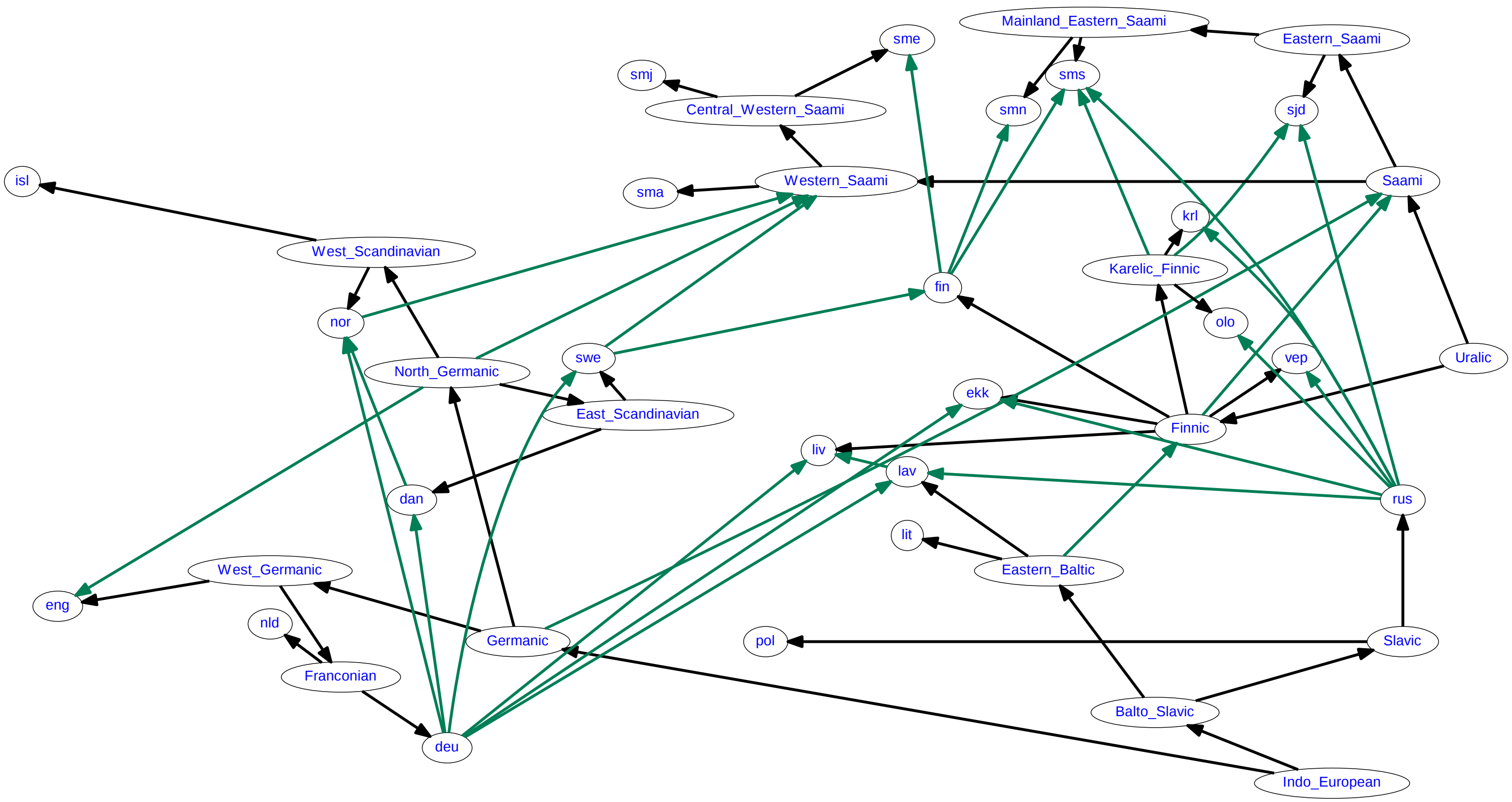
- the paths on which lexical material was inherited (i.e. a phylogenetic tree)
- the paths on which lexical material was borrowed (both among ancestral and living languages)
- taken together, all the paths on which lexical material has “flown” to produce the observable situation (**lexical flow**)

Simplifying assumptions taken in my approach:

- some phylogenetic tree is known (good inference methods exist)
- we have a usable reconstruction of the cognacy classes present at each proto-language (derived by historical linguists, or using some automated reconstruction method)

Phylogenetic Lexical Flow Inference: Example

Desired result for the region around the Baltic Sea:



Existing Phylogenetic Network Methods

Morrison (2011): two main types of phylogenetic network

- **data-display networks**
  - ▷ generalize unrooted trees
  - ▷ use additional virtual nodes to visualize conflicting signals
  - ▷ examples: median network, neighbor-net
- **evolutionary networks**
  - ▷ generalize rooted trees
  - ▷ all nodes represent some (ancestral) language
  - ▷ lateral connections are directed
  - ▷ examples: galled tree, galled network, hybridization network

Existing Phylogenetic Network Methods

Evolutionary network inference is still in its infancy:

- **probabilistic models** are very complex and need a lot of strong modeling assumptions; inference methods do not scale well to large networks, 7 species is the limit hit by Wen et al. (2016)
- models for more languages restrict the search space rather heavily, usually in terms of reticulation cycles
- **galled trees** do not allow node sharing between reticulation cycles ($\Rightarrow$ multiple donor languages not possible)
- **galled networks** allow reticulation cycles to share nodes, but only reticulation nodes, i.e. multi-way colliders are possible (BUT deu $\leftarrow$ eng $\rightarrow$ hin still not representable)
- **hybridization networks** are only slightly more general (they allow leaves as source languages)

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Causal Inference: Basic Idea

- algorithmic techniques to infer causal relationships between variables from observational data alone (Pearl, 2009)
- not possible for two variables: “correlation is not causation”
- but: interaction between more than two variables often provides hints about underlying causal scenario
- underlying theory (Reichenbach’s **Common Cause Principle**) states that whenever two variables are correlated, there must be either a directed causal path in exactly one direction, or a common cause (“no correlation without causation”)
- model causal scenarios as **causal DAGs** (directed acyclic graphs) over the variables, systematically exploit hints to infer properties of the underlying causal DAG

Conditional Independence and Causal Graphs

- core building block: a **conditional independence** relation
- $(X \perp\!\!\!\perp Y \mid Z)$ intuitively means:
  "any dependence between the variables X and Y can be explained by the influence of Z"
- PC algorithm: sequence of conditional independence tests reduces a complete graph to a **causal skeleton**, where no link can be explained away by conditioning on other variables
- removal of link $X - Y$ relies on finding a **separating set**, i.e. a set of variables $\{Z_1, \ldots, Z_n\}$ such that $(X \perp\!\!\!\perp Y \mid Z_1, \ldots, Z_n)$
- example: $(\mathit{sma} \perp\!\!\!\perp \mathit{fin} \mid \mathit{swe}, \mathit{Uralic})$

Unshielded Collider Criterion

- directionality inference on the causal skeleton
- for each pattern of the form $X - Z - Y$ (**unshielded triple**), ask whether the central variable was part of the separating set that was used for explaining away the link $X - Y$
- underlying idea: if Z was not necessary to explain away $X - Y$, this excludes all patterns except $X \rightarrow Z \leftarrow Y$ (a **v-structure**)
- reason: we would expect some information flow in all three scenarios $X \leftarrow Z \rightarrow Y$, $X \leftarrow Z \leftarrow Y$, and $X \rightarrow Z \rightarrow Y$
- this relies on a causal **faithfulness** assumption: we can measure $(X \perp\!\!\!\perp Y \mid Z)$ iff this is implied by the true causal graph
- example: *swe* – *fin* – *Fennic*, (*swe* $\perp\!\!\!\perp$ *Fennic*), i.e. Finnish not necessary to separate Swedish from Fennic, therefore *swe* $\rightarrow$ *fin* $\leftarrow$ *Fennic*

Propagating Directionality Information

- if all possible common causes are measured, the faithfulness assumption implies we can be sure to have detected exactly the true v-structures
- this provides an inference rule $X \rightarrow Z - Y \Rightarrow X \rightarrow Z \rightarrow Y$
- the PC algorithm uses this rule to **propagate directionality information** through the graph, in many case assigning a direction to each node in the causal skeleton
- example: Glottolog gives us $\mathit{Franconian} \rightarrow \mathit{deu}$, we found it impossible to separate $\mathit{deu} - \mathit{liv}$, but $(\mathit{Franconian} \not\perp\!\!\!\perp \mathit{liv})$ and $(\mathit{Franconian} \perp\!\!\!\perp \mathit{liv} \mid \mathit{deu})$, no v-structure, therefore $\mathit{deu} \rightarrow \mathit{liv}$

Conditional Independence between Languages

- joint information measure for sets of languages $L_1, \ldots, L_n$:

$$R(L_1, \ldots, L_n) := \left| \bigcup_{i=1}^{n} cog(L_i) \right|$$

- from this we get **conditional mutual information between languages** given a set of languages $\mathbf{S} := \{S_1, \ldots, S_n\}$:

$$I(L_i, L_j; \mathbf{S}) := R(L_i, S_1, \ldots, S_n) + R(L_j, S_1, \ldots, S_n) \\ - R(L_i, L_j, S_1, \ldots, S_n) - R(S_1, \ldots, S_n)$$

- R is **submodular**; Steudel et al. (2010) show that checking for non-zero I gives us a consistent conditional independence test
- intuitively: how many cognates between L_i and L_j cannot be explained away by also being cognate to a word in one of the languages in **S**?

Skeleton Inference: Standard PC variants

- testing exponentially many possible sepsets: intractable
- decisive ideas behind **PC algorithm** (Spirtes et al., 2000):
  - ▷ search for minimal separating sets by increasing cardinality
  - ▷ any information flow must involve the remaining neighbors of either node, we only need to consider separating set candidates composed of such neighbors
- **PC*** variant: only build candidate sepsets from neighbors on connecting paths between X and Y

Skeleton Inference: Flow separation criterion

Explicit discrete information units allow us to

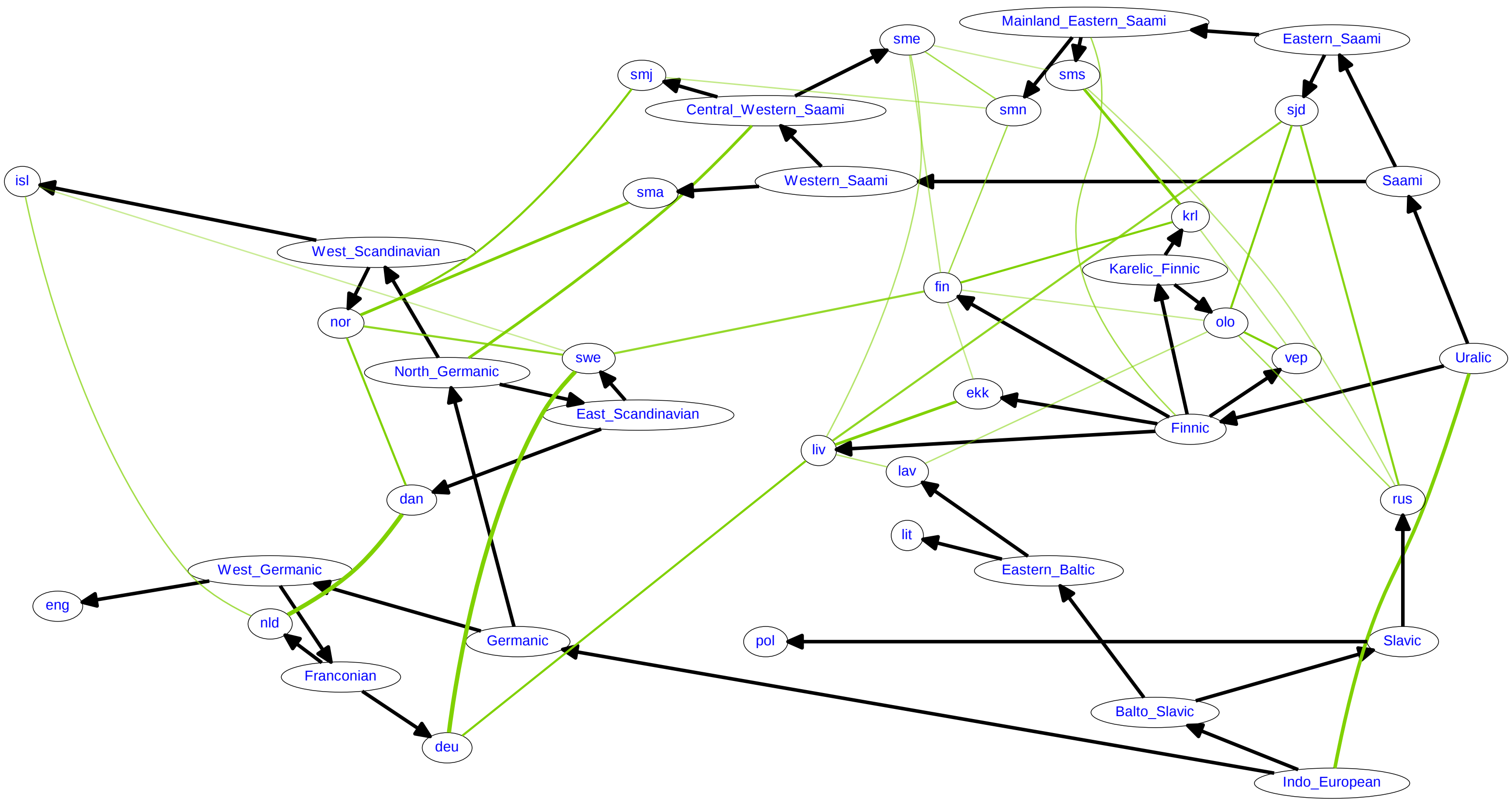
- compose all separating set candidates of connecting paths (not just neighbors, but all nodes on the paths)
- decide for every single shared cognate set whether the sepset includes a path by which the shared material could have traveled

This leads to a **Flow Separation (FS)** criterion:

- separation only occurs if there are is a concrete alternative path for every single cognate shared between X and Y
- some threshold is still necessary in practice to correct for dirty cognacy judgments, and semantic change withering away the traces; 2% in my tests (meaning that contacts which replaced less than 20 out of 1000 words will never appear in the network)

Phylogenetic Lexical Flow Inference: Example

Example result of FS in region around the Baltic Sea:



Directionality Inference: Standard variants

- **PC**: v-structure $X \rightarrow Z \leftarrow Y$ iff Z not needed to separate X, Y, i.e. there is one separating set S with $Z \notin S$
- **Stable PC**: compare how many minimal sepsets contain or do not contain Z, make decision by majority rule
- Despite the name, all PC variants have stability problems! Workaround in Dellert (2016):
  - ▷ aggregate evidence from different unshielded triples into a **Triangle Sum Score (TSS)** measuring the signal on each link
  - ▷ this causes some errors to cancel out, arrows with high aggregate scores are much more reliable
  - ▷ TSS can be used independently of the skeleton, the two inference steps do not depend on each other! (more stability)

Directionality Inference: Unique Flow Ratio (UFR)

New alternative:

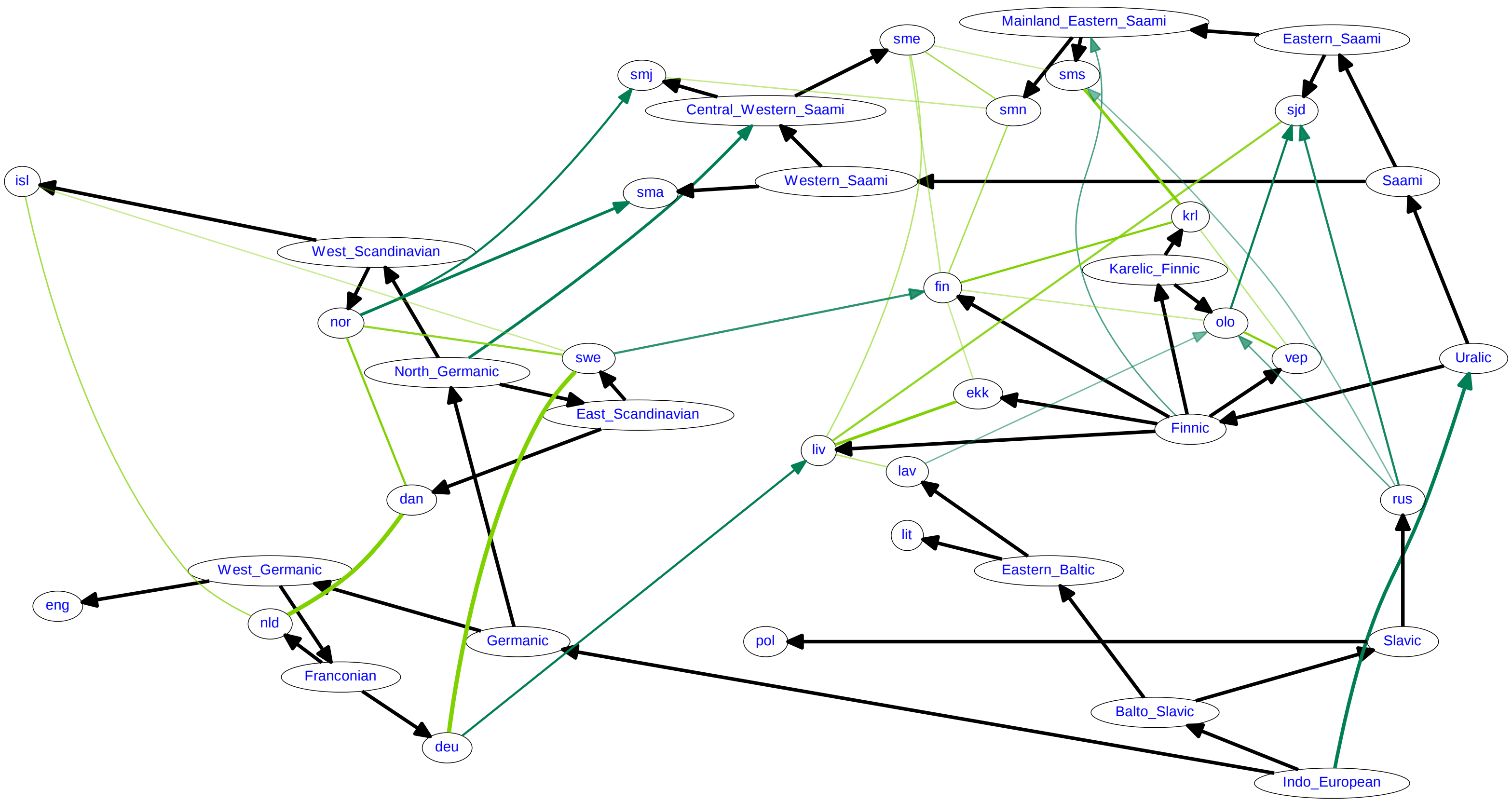
- define a score for unshielded triples for making the collider decisions, based on the same intuitions plus a flow criterion
- propagate the decisions by the PC propagation rules

Details of the **Unique Flow Ratio (UFR)** score:

- idea: quantify the notion of "Z needed to remove X — Y"
- let cog_{XYZ} be the cognates shared between between X, Y, Z
- cog_{XYZ*}: the cognates which no path excluding Z could have transported between X and Y (**unique flow**)
- $ufr_1 := \frac{\frac{|cog_{XYZ*}|}{\min(|cog_X|,|cog_Y|,|cog_Z|)}}{\frac{|cog_{XZ}|}{\min(|cog_X|,|cog_Z|)} \cdot \frac{|cog_{YZ}|}{\min(|cog_Y|,|cog_Z|)}}$ ("as much UF as expected?")
- $ufr_2 := cog_{XYZ*} / cog_{XYZ}$ ("how relevant is flow through Z?")
- $ufr := ufr_1 \cdot ufr_2$, v-structures will typically have $ufr < 0.02$

Phylogenetic Lexical Flow Inference: Example

Example result of TSS in region around the Baltic Sea:



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Generating Testset Data by Simulation

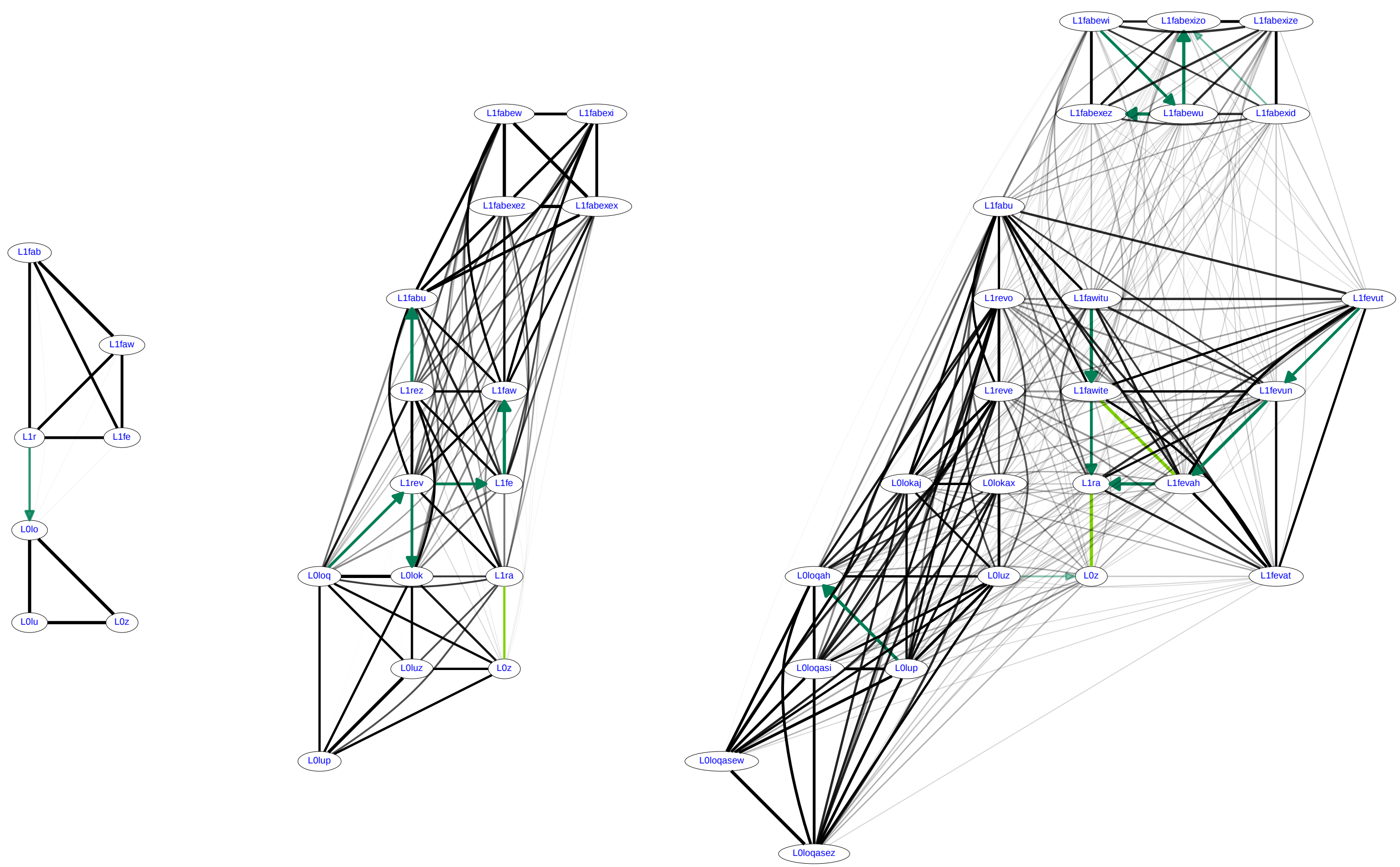
Advantages of using simulations:

- arbitrary amount of test data
- abstract away from problems caused by error-prone cognate detection, tree inference, and ancestral state reconstruction

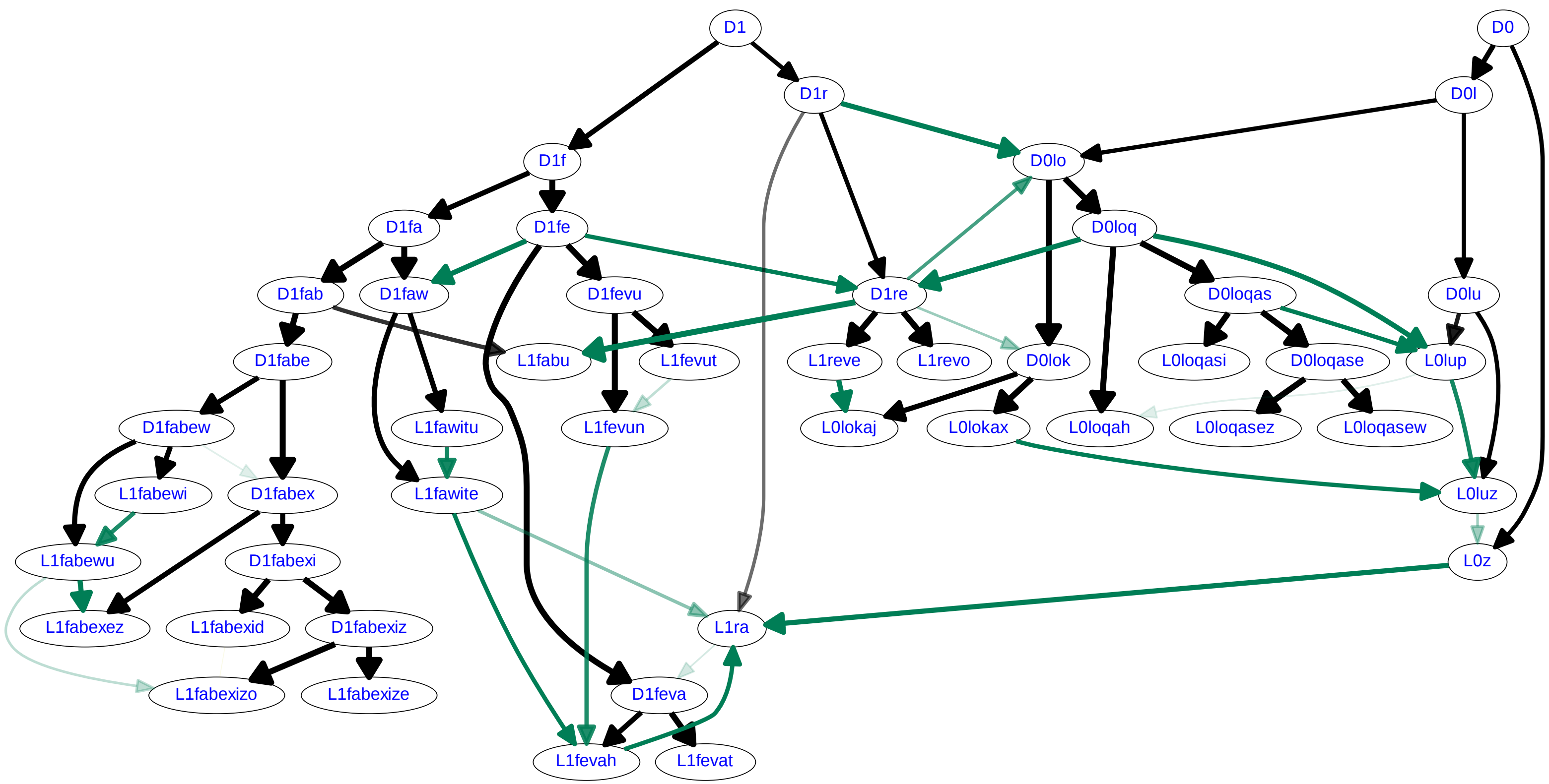
Core design decisions of my simulation model:

- languages split at random intervals, filling a continent
- a language does not become extinct without reason, it only gets replaced if a neighboring language splits into its territory
- we explicitly model lexical replacement in each language (longer splits will lead to less cognate set overlap)
- monodirectional contact channel can open at any time between neighbors, on which cognate IDs are randomly copied over
- every single event modifying the data is tracked, we retain access to complete knowledge

Example: The Simulation Process



Example: A Simulated Flow Network



Skeleton Inference: Evaluation Measures

Evaluation measures can be defined in a very straightforward way:

- **skeleton recall**: which percentage of the lateral connections in the gold standard are also in the inferred skeleton?
- **skeleton precision**: which percentage of the inferred lateral connections are justified by the gold standard?
- **skeleton f-score**: harmonic mean of skeleton precision and recall, i.e. $2 \cdot \frac{SkPr \cdot SkRc}{SkPr + SkRc}$

Skeleton Inference: Comparison on 5 scenarios

	PC	PC*	FS
skeleton recall	0.894	**0.972**	0.897
skeleton precision	0.648	0.687	**0.763**
skeleton f-score	0.752	0.805	**0.825**

- skeletons tend to include almost all relevant lateral connections, but about one fourth of lateral connections are spurious
- clear ranking: PC* better than PC, and FS more precise
- for all the experiments, the flow separation-based skeleton and separating sets will be used

Directionality Inference: Evaluation Measures

Evaluation measures for directionality more difficult to define:

- problem for defining precision and recall:
  we have three options in both the gold standard and the result!
- mapping these to the four basic categories is non-trivial
- my proposal for counting the instances:

	$\rightarrow$ **in result**	$\leftarrow$ **in result**	$\leftrightarrow$ **in result**
$\rightarrow$ **in standard**	*tp* + *tn*	*fp* + *fn*	*tp* + *fp*
$\circ\!\!\rightarrow$ **in standard**	*tp*	*fn*	*tp* + *tp*
$\leftrightarrow$ **in standard**	*tp* + *fn*	*tp* + *fn*	*tp* + *tp*

- **arrow recall**: $tp/(tp + fn)$, as usual
- **arrow precision**: $tp/(tp + fp)$, as usual
- **arrow f-score**: harmonic mean of arrow precision and recall, i.e. $2 \cdot \frac{ArPr \cdot ArRc}{ArPr + ArRc}$

Directionality Inference: Comparison on 5 scenarios

Comparison on the best skeleton (derived by FS):

	PC	Stable PC	UFR	TSS
arrow recall	0.758	**0.805**	0.798	0.637
arrow precision	0.878	0.854	0.866	**0.909**
arrow f-score	0.814	0.829	**0.831**	0.749

- directionality inference on the true arcs is quite satisfactory
- clearly the worst method: triangle score sum,
  though the fewer arrows it infers are quite reliable
- vanilla PC quite reasonable, not much worse than best variants
- stable PC and UFR best, very comparable in performance

Acknowledgments

- Gerhard Jäger (supervision)
- Igor Yanovich (detailed discussions)
- all other members of the EVOLAEMP team (feedback at many stages)
- the ERC (Advanced Grant 324246)

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Directionality Inference: Triangle Score Sum (TSS)

Details of the **Triangle Score Sum (TSS)** score:

- consider each unshielded triple $l_1 \rightarrow l_2 \leftarrow l_3$
- define $w(l_1 \rightarrow l_2; l_3) := \frac{|cog(l_1) \cap cog(l_2)| \cdot |cog(l_2) \cap cog(l_3)|}{|cog(l_2)|}$, i.e. the cognate overlap between l_1 and l_3 we would have expected if the true pattern had been $l_1 \leftarrow l_2 \rightarrow l_3$ or $l_1 \leftarrow l_2 \leftarrow l_3$
- aggregate from all triples into $sc(l_1 \rightarrow l_2) := \sum_{l_3} w(l_1 \rightarrow l_2; l_3)$, use threshold on $sc(l_1 \rightarrow l_2)/sc(l_2 \rightarrow l_1)$ to make decision