

A SEARCH SET MODEL OF PATH TRACING IN GRAPHS

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MSc. Presentation

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INTRODUCTION

Background & Motivation, Our Approach, Thesis Contributions

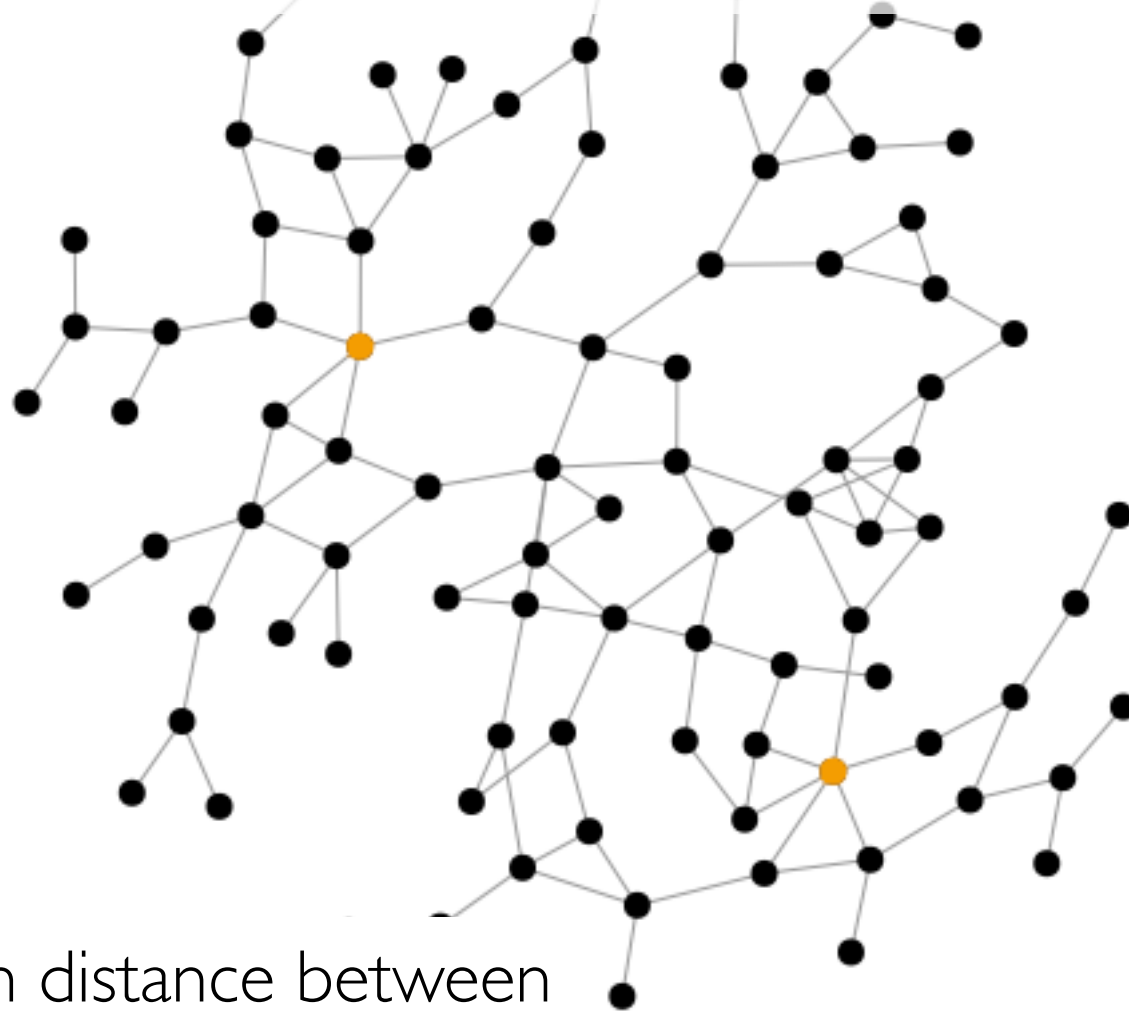
BACKGROUND & MOTIVATION

Path-Tracing

- Widely studied abstract task in previous work
[Ghoniem et al., 2002][Lee et al., 2006]
- Common task in real-world uses of graphs showing networks of relationships

BACKGROUND & MOTIVATION

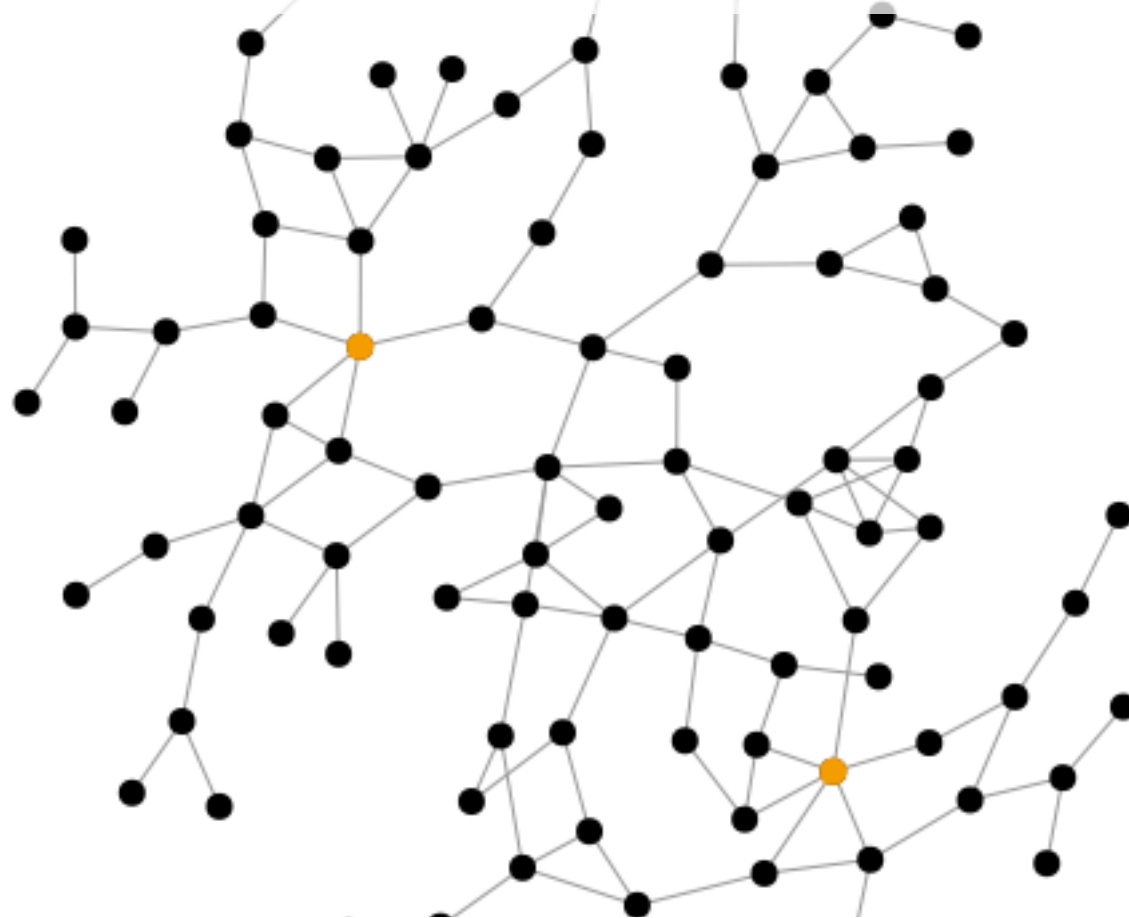
Examples: Real World Path-Tracing



How much distance between
me and Kevin Bacon?

BACKGROUND & MOTIVATION

Examples: Real World Path-Tracing



Or - How many potential disease transmission paths between two people?

BACKGROUND & MOTIVATION

Understanding Path Tracing Difficulty

- In graph drawing, *layout quality* judged by measuring *factors*
 - E.g., Edge-edge crossings
- Many automatically computable factors proposed
 - Minimize edge-edge crossings
 - maximize angular resolution of edges at nodes
 - minimize total edge lengths
 - ...



BACKGROUND & MOTIVATION

Understanding Path Tracing Difficulty

- Subsequent work has begun investigating how factors impact **graph readability** for humans
[Purchase et al., 1995] [Purchase, 1997] [Purchase, 2002] [Körner, 2004] [Huang et al., 2005] [van Ham & Rogowitz, 2008] [Dwyer et al., 2009] [Huang, 2011] [Huang & Huang, 2011] [Körner, 2011] [Purchase et al., 2012] ...
- Edge-edge crossings commonly cited as **most important**
 - despite mixed findings

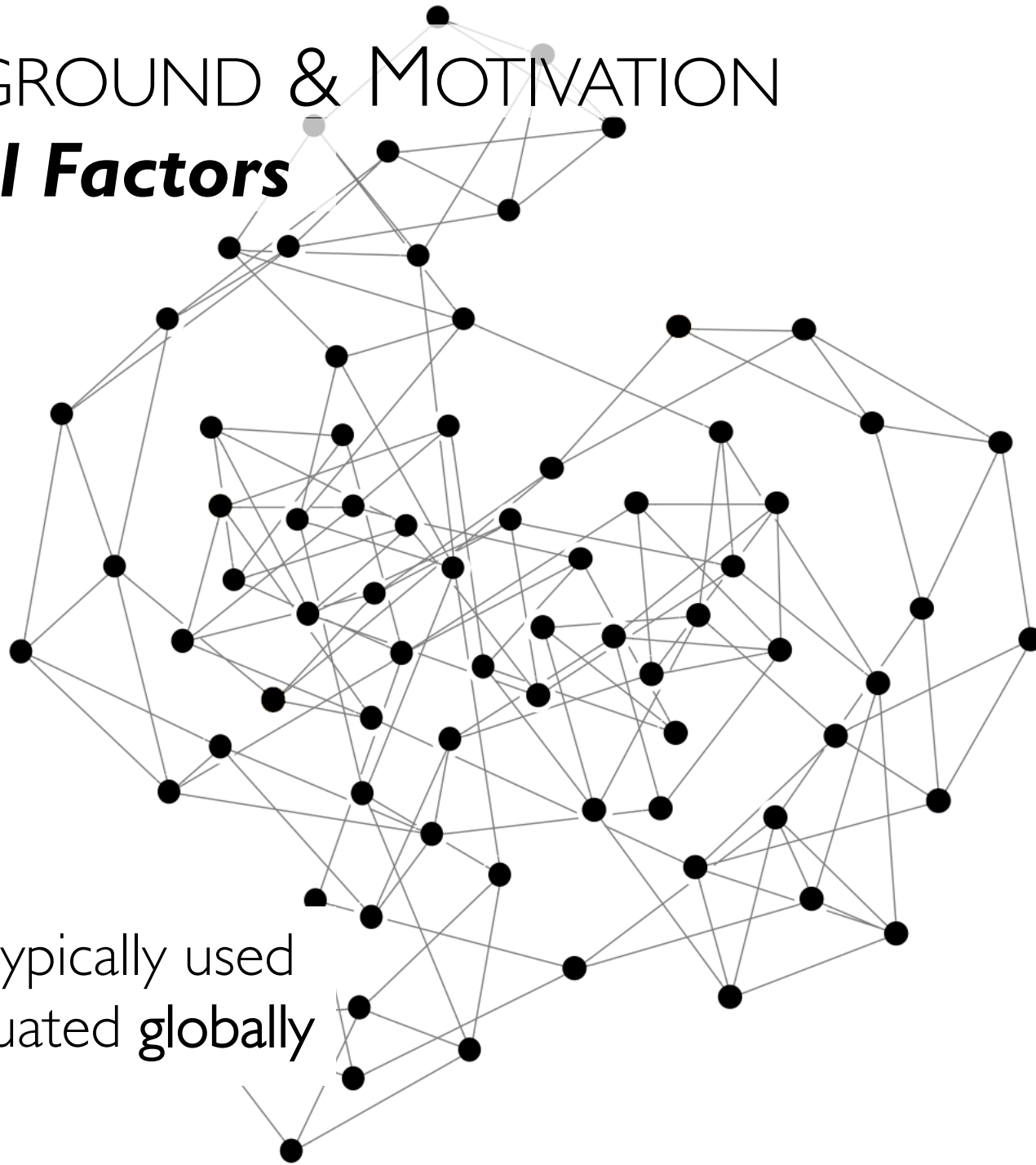
BACKGROUND & MOTIVATION

Understanding Path Tracing Difficulty

- What makes one path more difficult to follow than another is still **poorly understood**

BACKGROUND & MOTIVATION

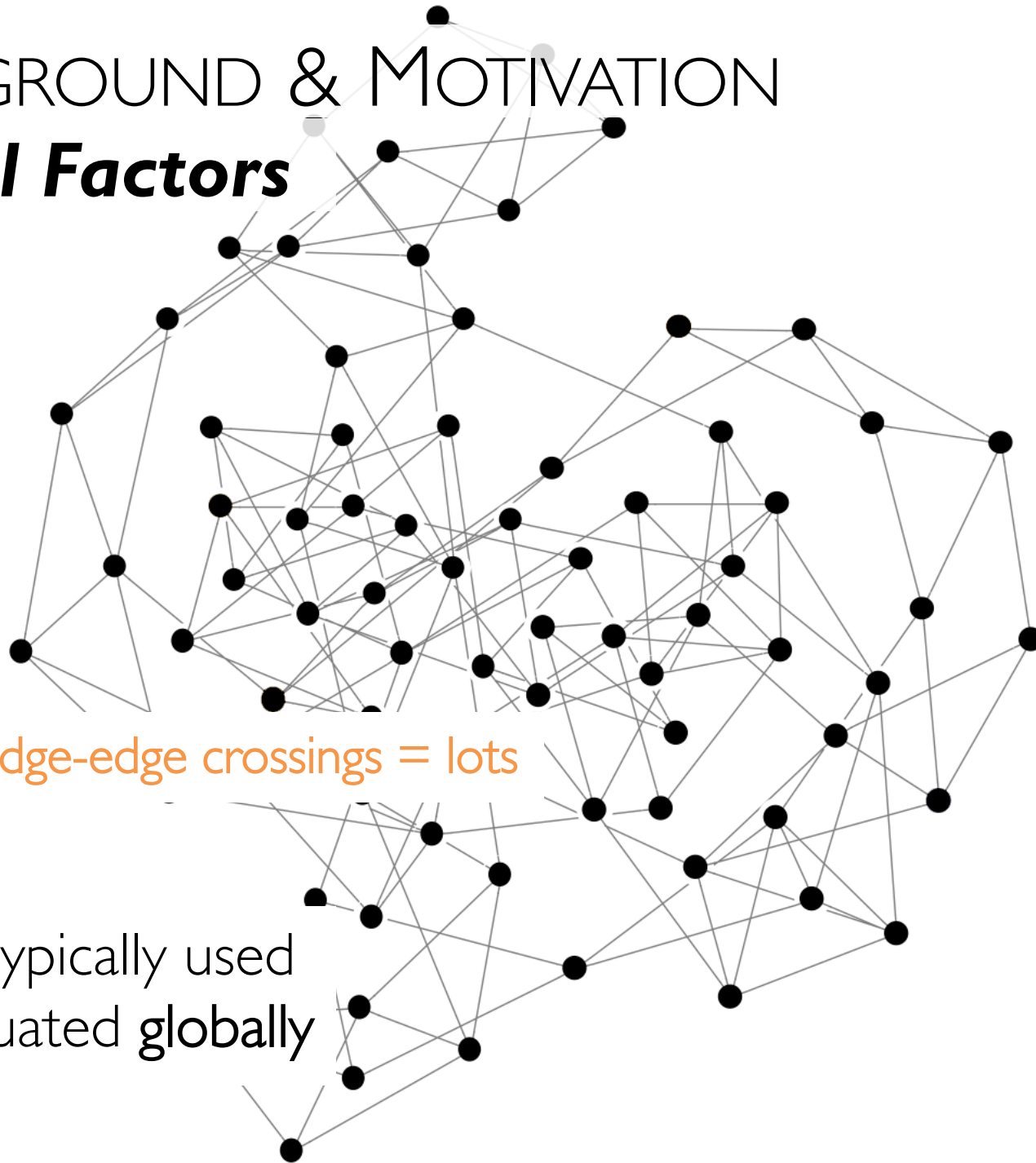
Global Factors



Factors typically used
and evaluated **globally**

BACKGROUND & MOTIVATION

Global Factors

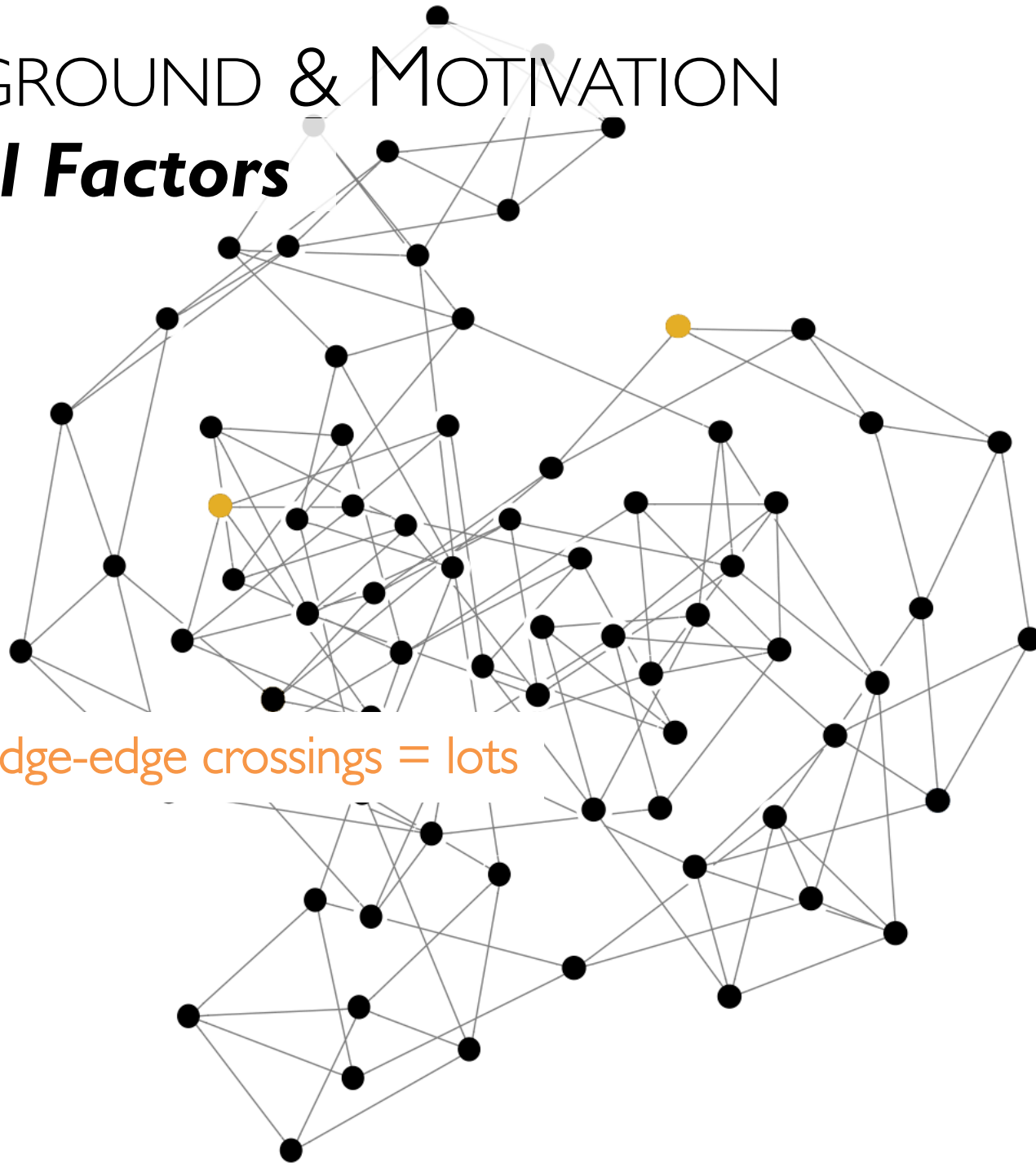


global edge-edge crossings = lots

Factors typically used
and evaluated **globally**

BACKGROUND & MOTIVATION

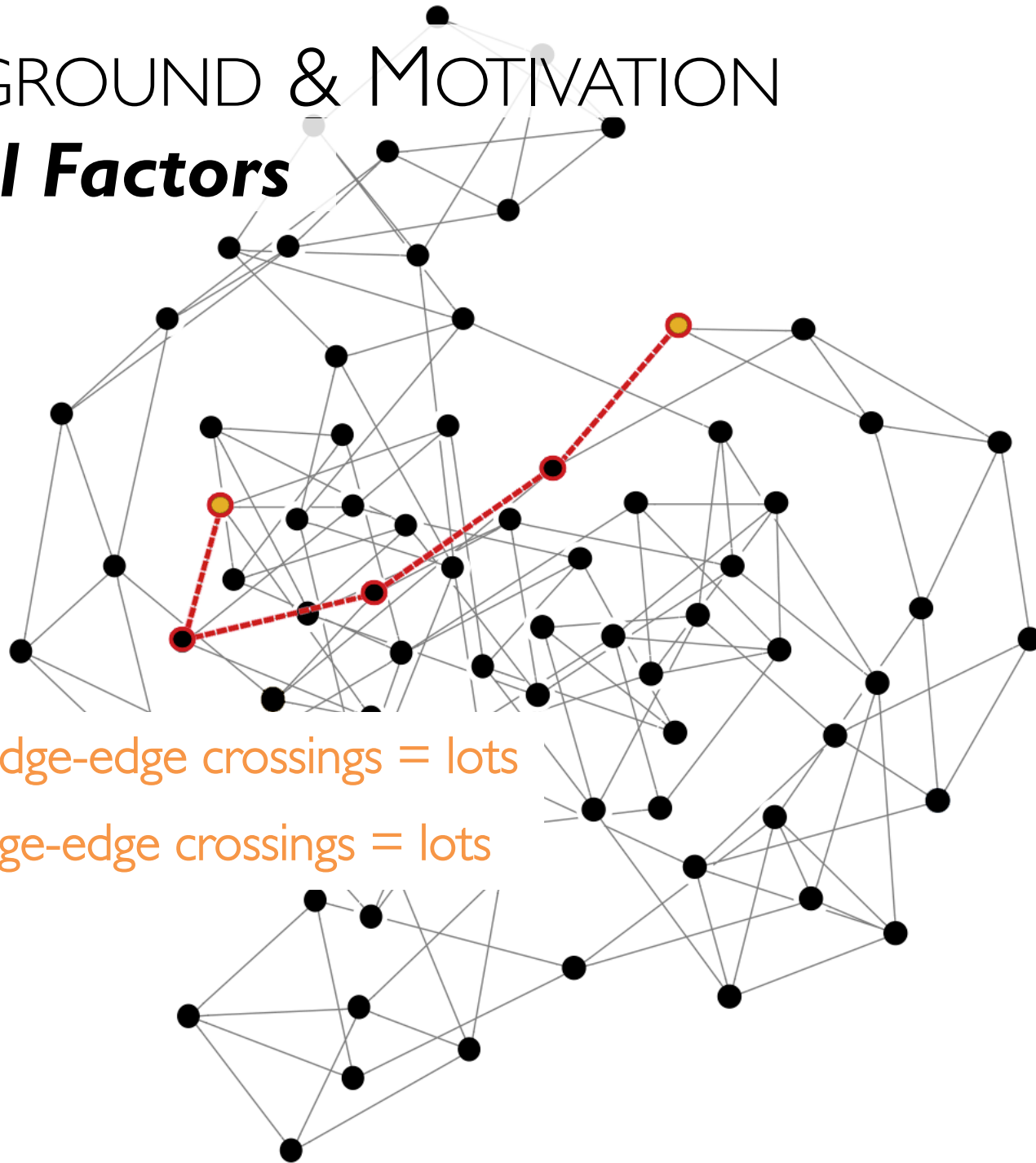
Global Factors



global edge-edge crossings = lots

BACKGROUND & MOTIVATION

Global Factors

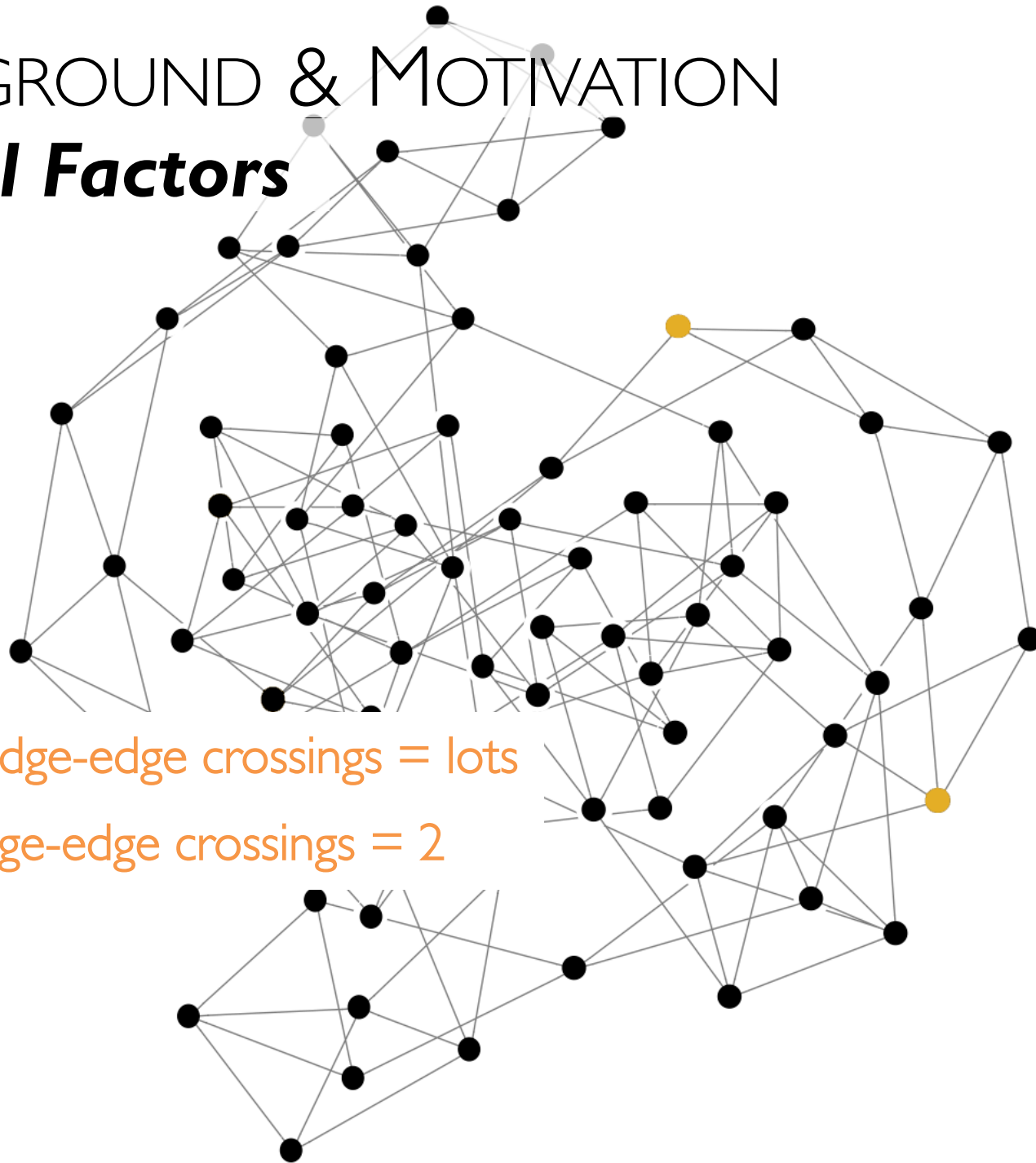


global edge-edge crossings = lots

local edge-edge crossings = lots

BACKGROUND & MOTIVATION

Global Factors

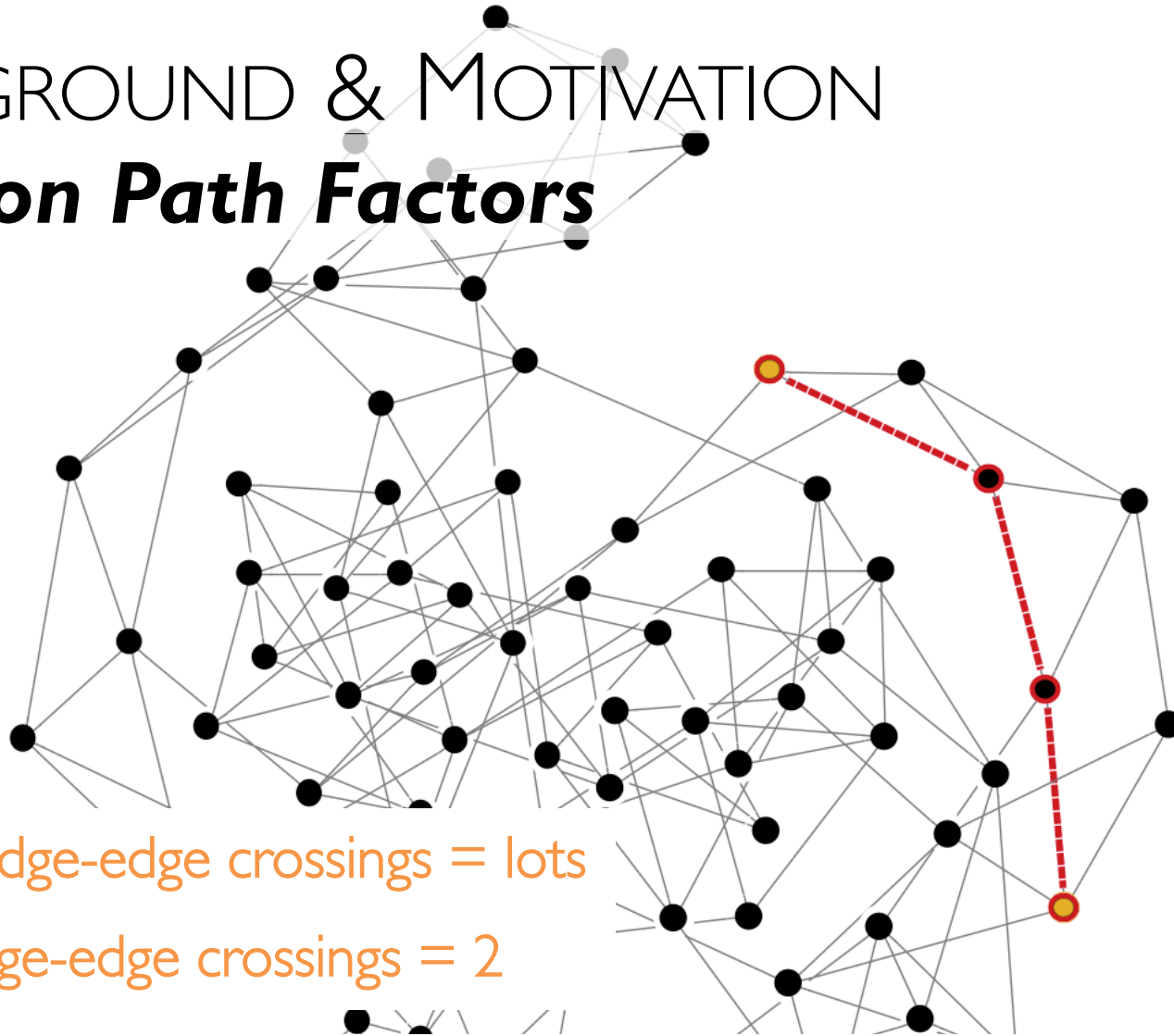


global edge-edge crossings = lots

local edge-edge crossings = 2

BACKGROUND & MOTIVATION

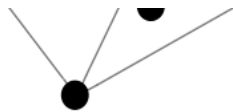
Solution Path Factors



global edge-edge crossings = lots

local edge-edge crossings = 2

For path tracing tasks, solution path factors much better predictors of difficulty [Ware et al., 2002]



OUR APPROACH

Goldilocks Problem

- Global level often takes too much into account
- But solution-path level may take too little into account
 - Does not account for everything relevant to task
- Just right?
 - What if we measure factors on the set of paths a user searches (*search set*) while completing a task?

OUR APPROACH

Predicting a Search Set

Could we predict the set of paths that a user is likely to search while path tracing?

OUR APPROACH

Uses for a Predicted Search Set

- Being able to predict the paths a user searches would be useful ...
 - For design of interaction techniques
 - For new automatic graph layout algorithms
 - For improving measurement of factors that affect graph readability
 - As a characterization of how users read graphs

OUR APPROACH

Uses for a Predicted Search Set

- Being able to predict the paths a user searches could be useful ...
 - For design of interaction techniques
 - For new automatic graph layout algorithms
 - *For improving measurement of factors that affect graph readability*
 - *As a characterization of how users read graphs*

THESIS CONTRIBUTIONS

- (1) The concept of a search set in path tracing
- (2) A detailed characterization of path tracing behaviours
- (3) A predictive model of a search set
- (4) A multiple regression analysis using search set to measure factors that affect graph readability

THE SEARCH SET CONCEPT

Related Work, Geodesic Tendency, Research Questions

RELATED WORK

Human Behaviour & Graph Readability

- Some previous work observed human behaviour when interacting with graphs
 - Identify new factors
[van Ham & Rogowitz, 2008] [Dwyer et al., 2009] [Purchase et al., 2012]
 - Understand how factors operate through eye tracking
[Körner, 2004] [Huang et al., 2009] [Huang., 2013]

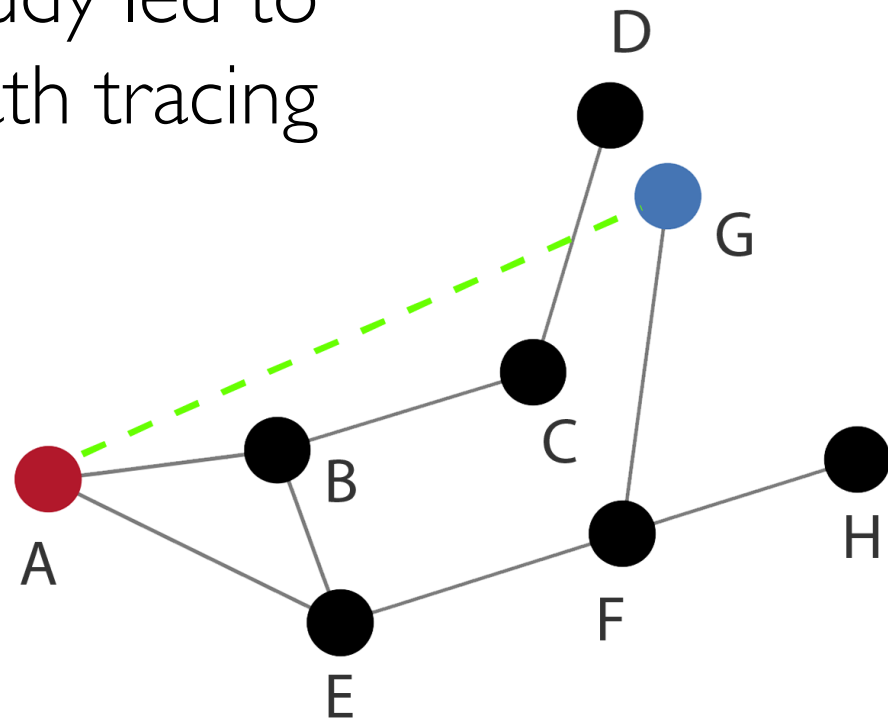
RELATED WORK

Geodesic Tendency

- One eye tracking study led to identification of a path tracing behaviour:

geodesic tendency

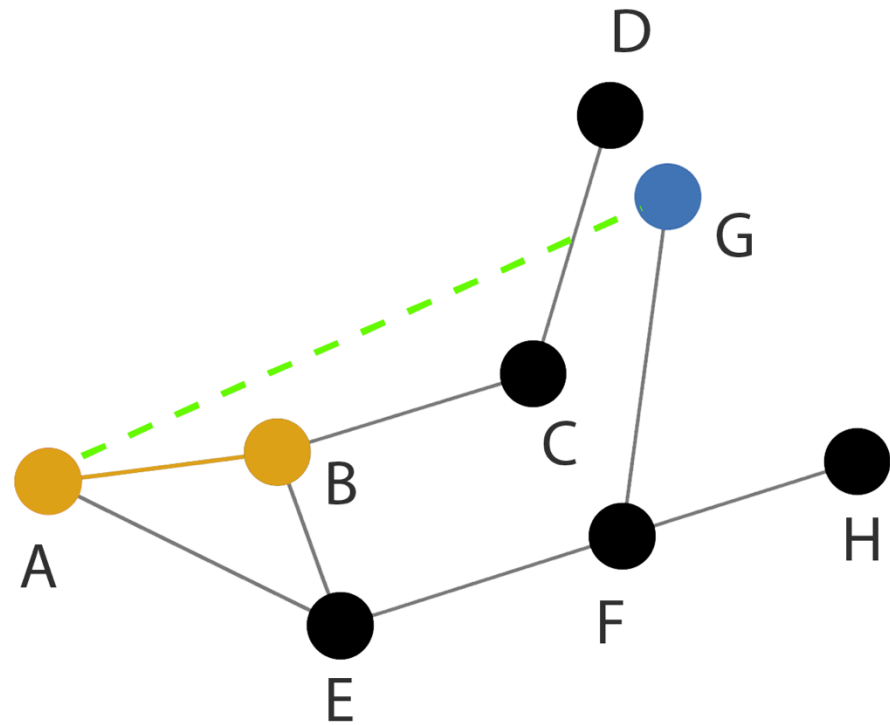
[Huang et al., 2009]



RELATED WORK

Geodesic Tendency

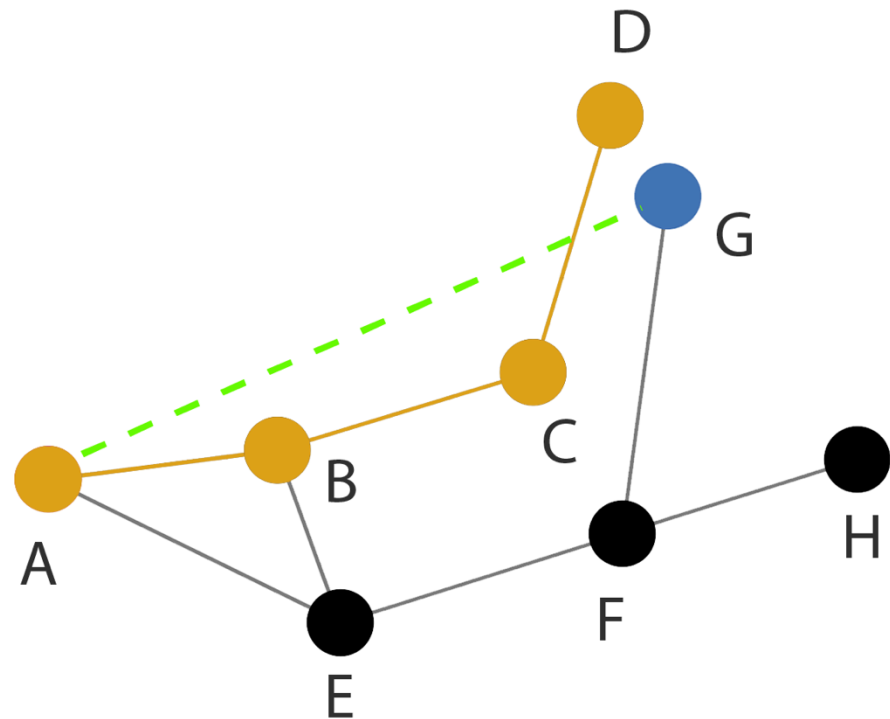
I. A B



RELATED WORK

Geodesic Tendency

I. A B C D

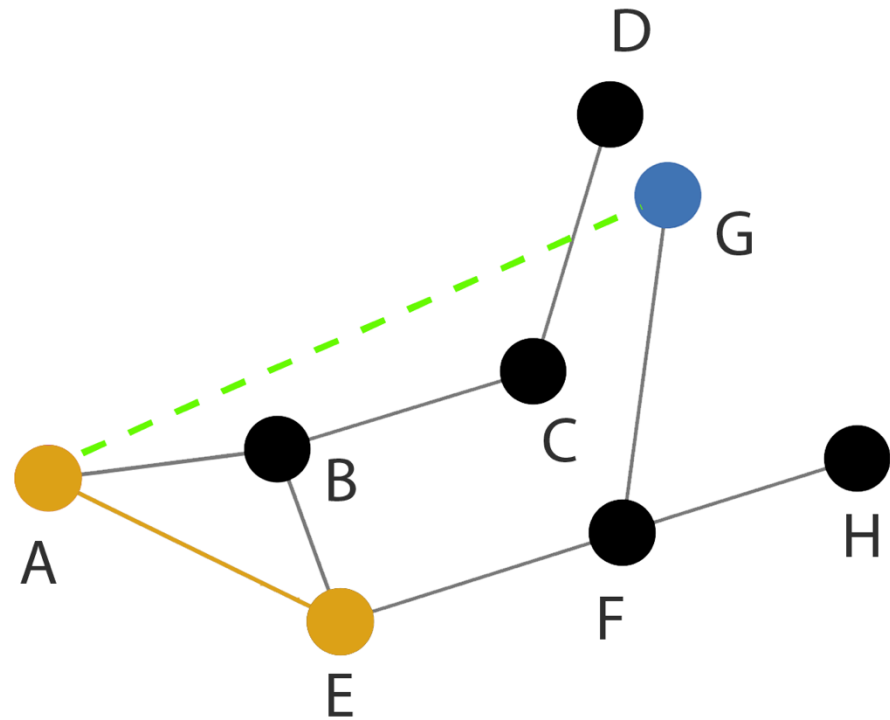


RELATED WORK

Geodesic Tendency

2. A E

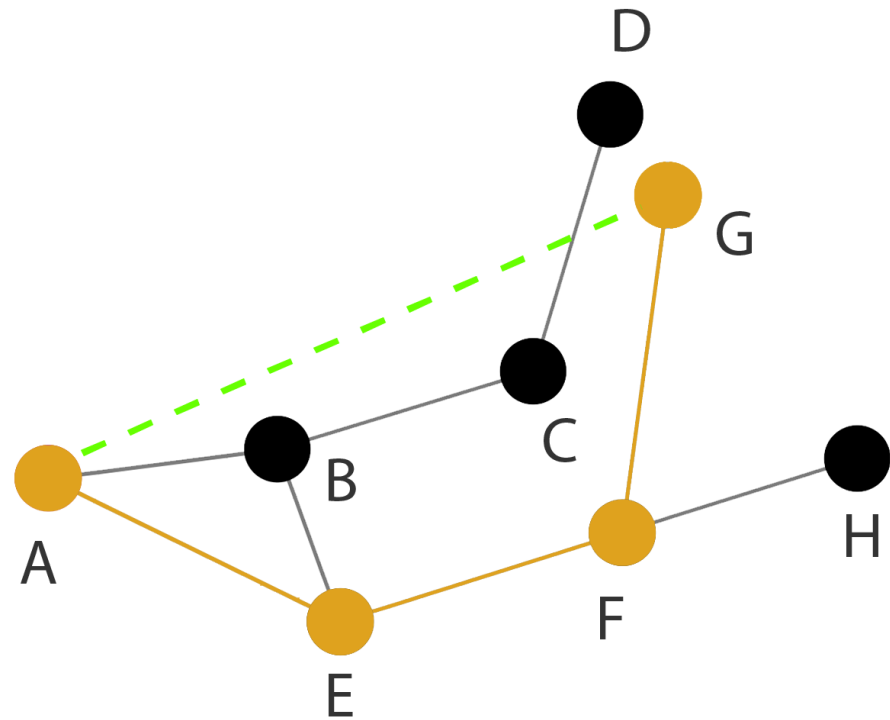
Divert from closest to geodesic for first hop...



RELATED WORK

Geodesic Tendency

2. A E F G



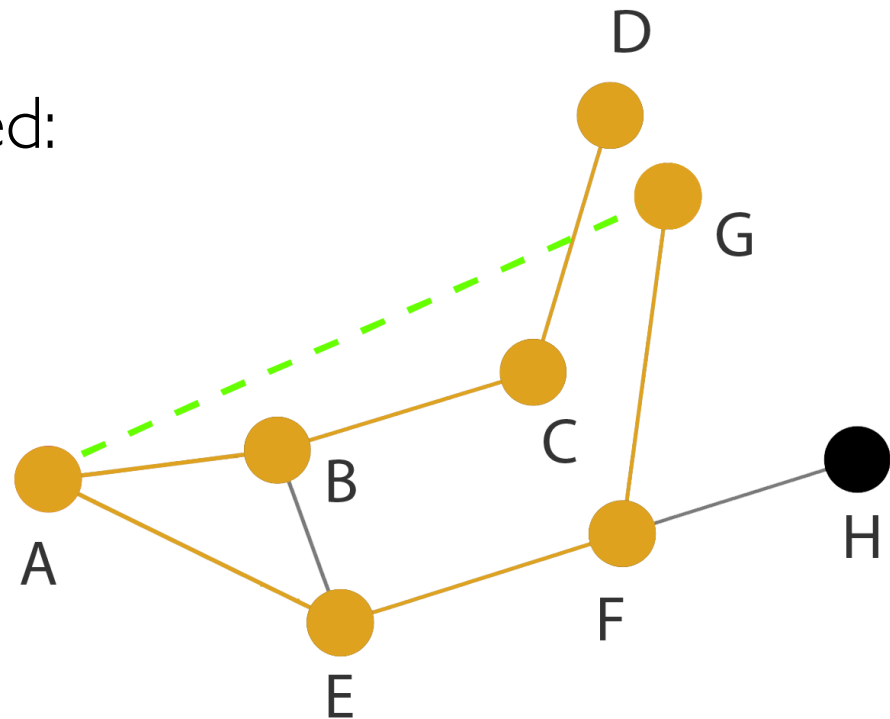
RELATED WORK

Geodesic Tendency

Set of likely paths searched:

1. A B C D

2. A E F G

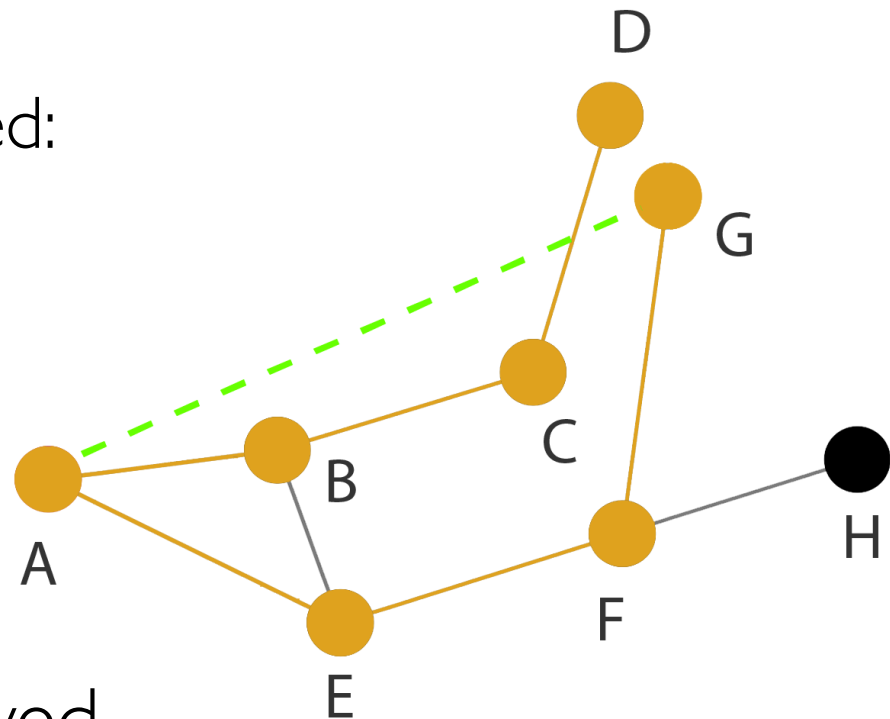


RELATED WORK

Geodesic Tendency

Set of likely paths searched:

1. A B C D
2. A E F G



But early piloting showed
geodesic tendency only part of story...

THE SEARCH SET CONCEPT

Research Questions

(Q1) can we identify distinct path tracing behaviours?

(Q2) how common are these behaviours?

(Q3) can we predict a search set based on these behaviours?

(Q4) how much improvement from measuring factors on search set?

OBSERVATIONAL USER STUDY

Study Design, Collected Data, Analysis Approach

OBSERVATIONAL USER STUDY

Design

- 12 participants
 - all students; ages 20–33, M=23.4, 4 females;
- Interface:
Graphs displayed on Cintiq tablet
- Primary Task:
Find shortest path between red and blue nodes
- Secondary Task:
Trace progress by hovering nodes with tablet pen



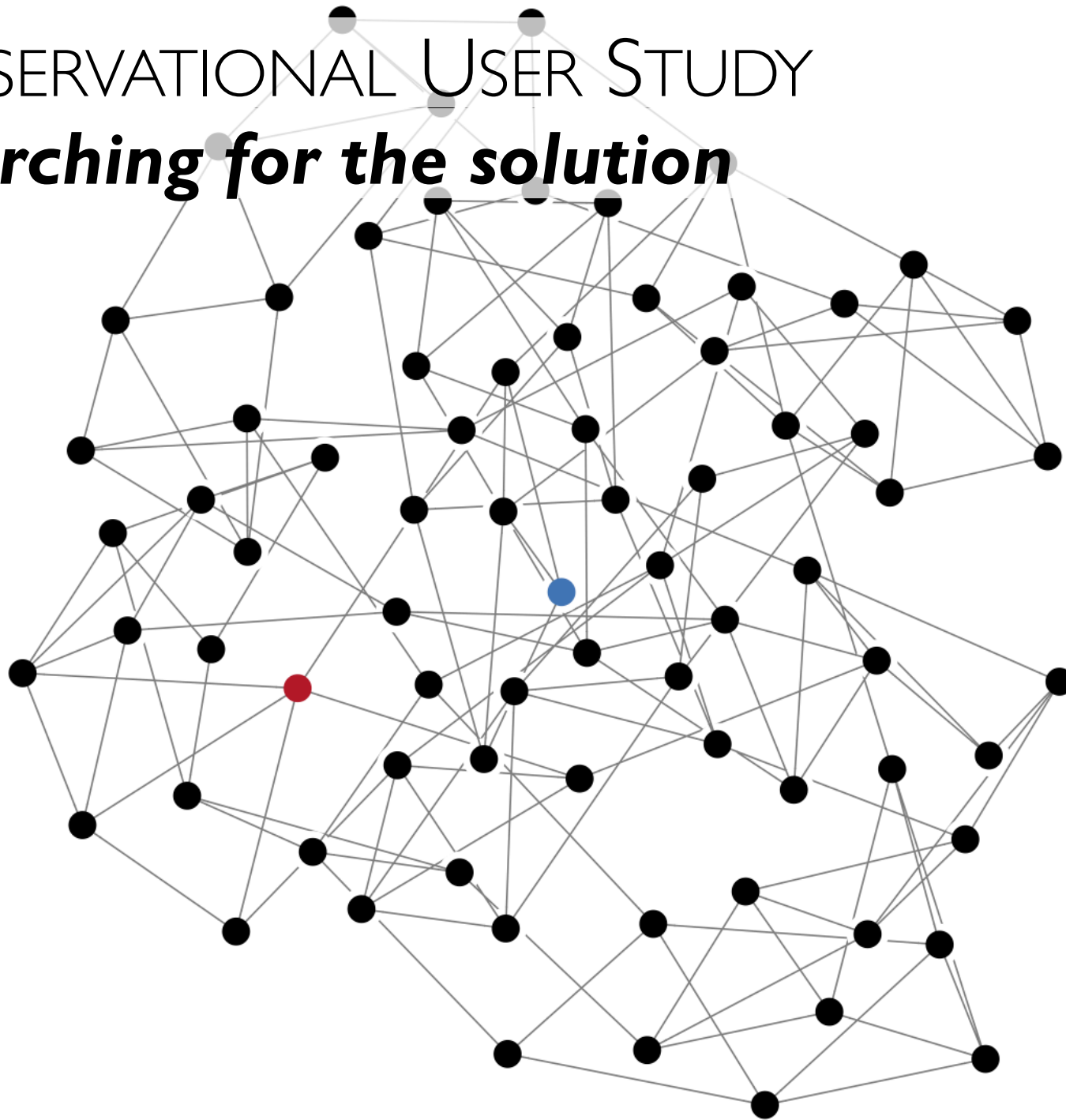
OBSERVATIONAL USER STUDY

Design

- 144 trials
 - split into two sessions (~1.5 hours each)
- 1 unique graph shown per trial
 - one shortest path in each graph
 - two phases:
 - (1) find solution path
 - (2) demonstrate solution path

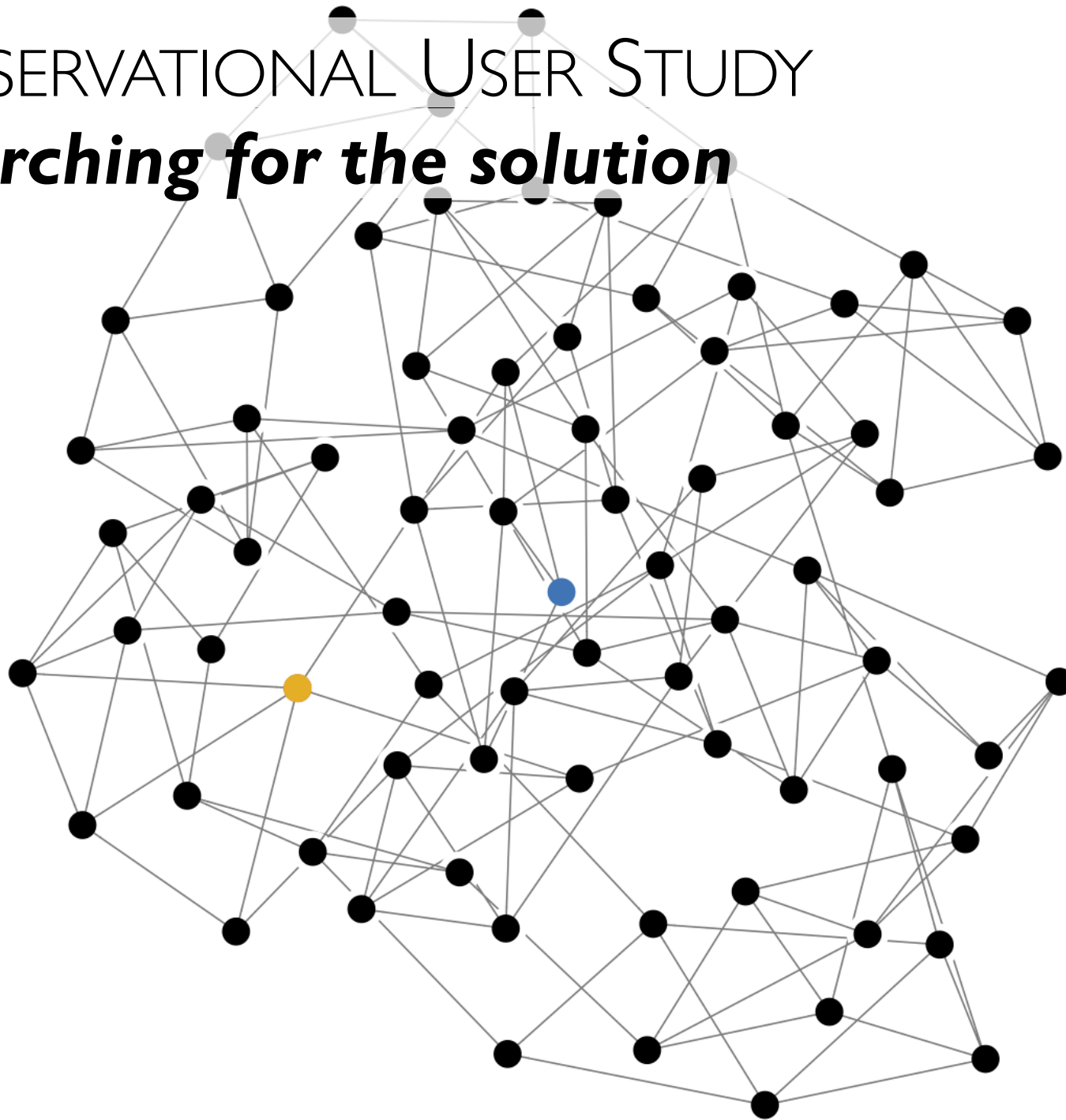
OBSERVATIONAL USER STUDY

Searching for the solution



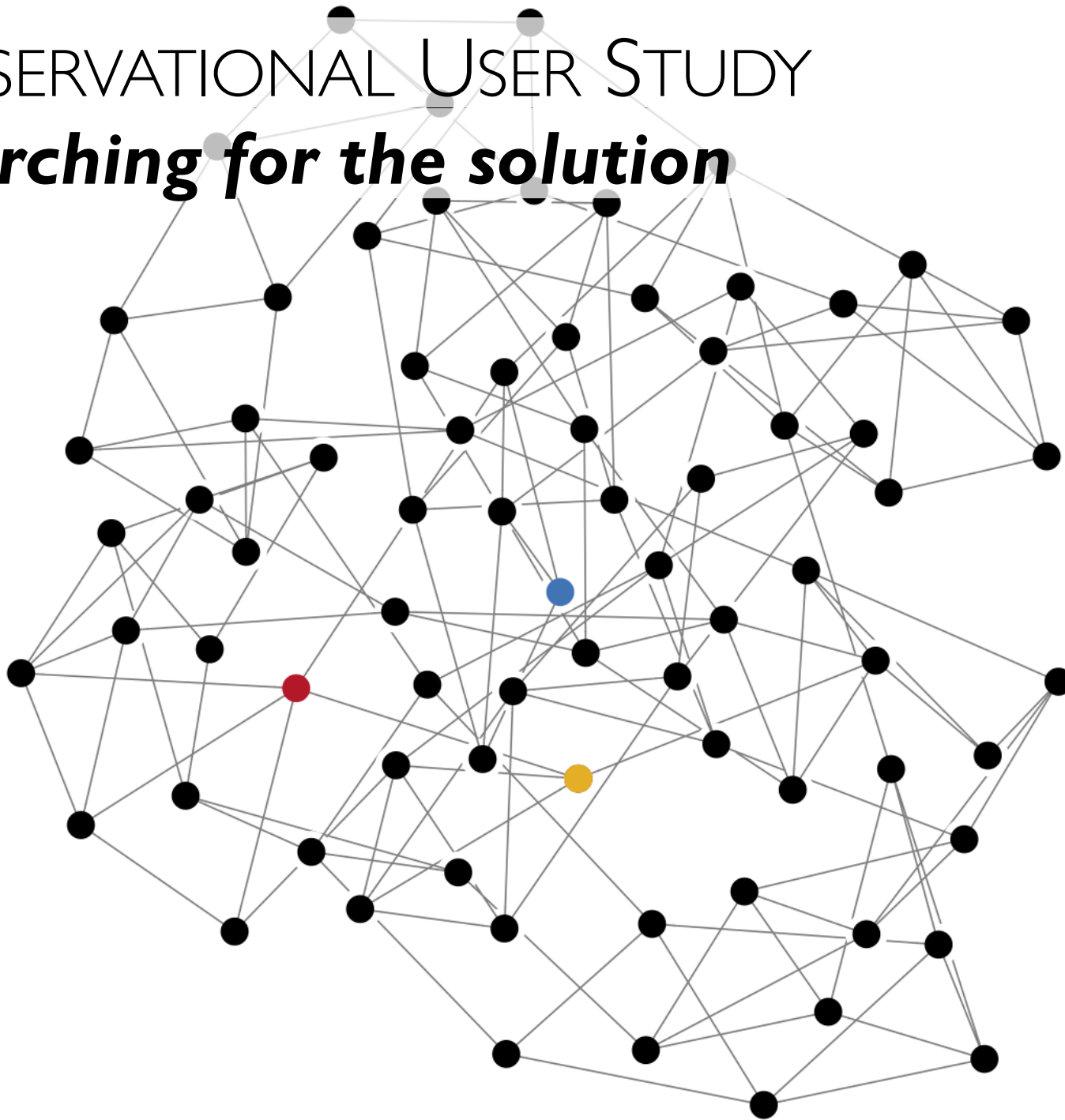
OBSERVATIONAL USER STUDY

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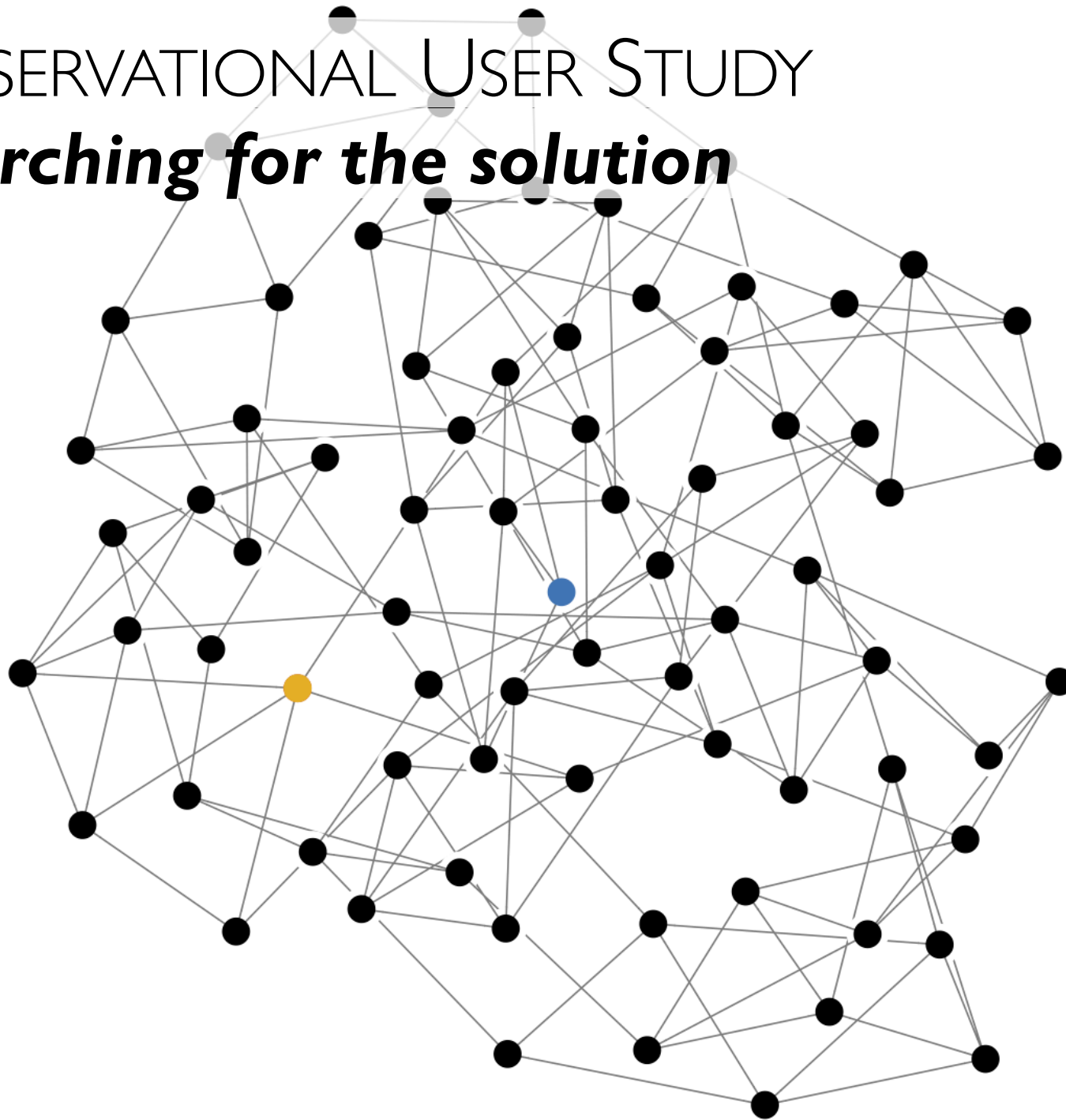
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Searching for the solution



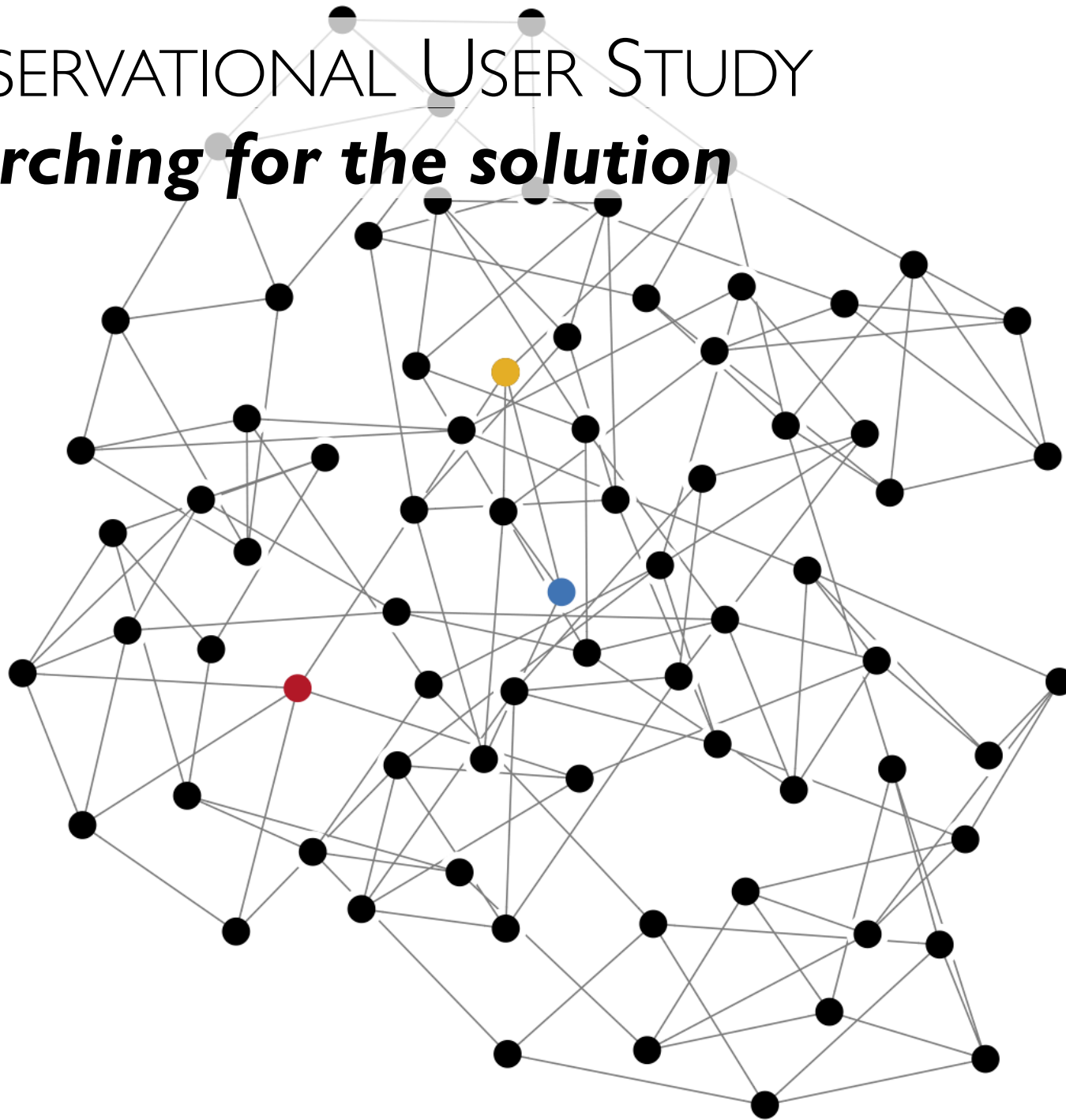
OBSERVATIONAL USER STUDY

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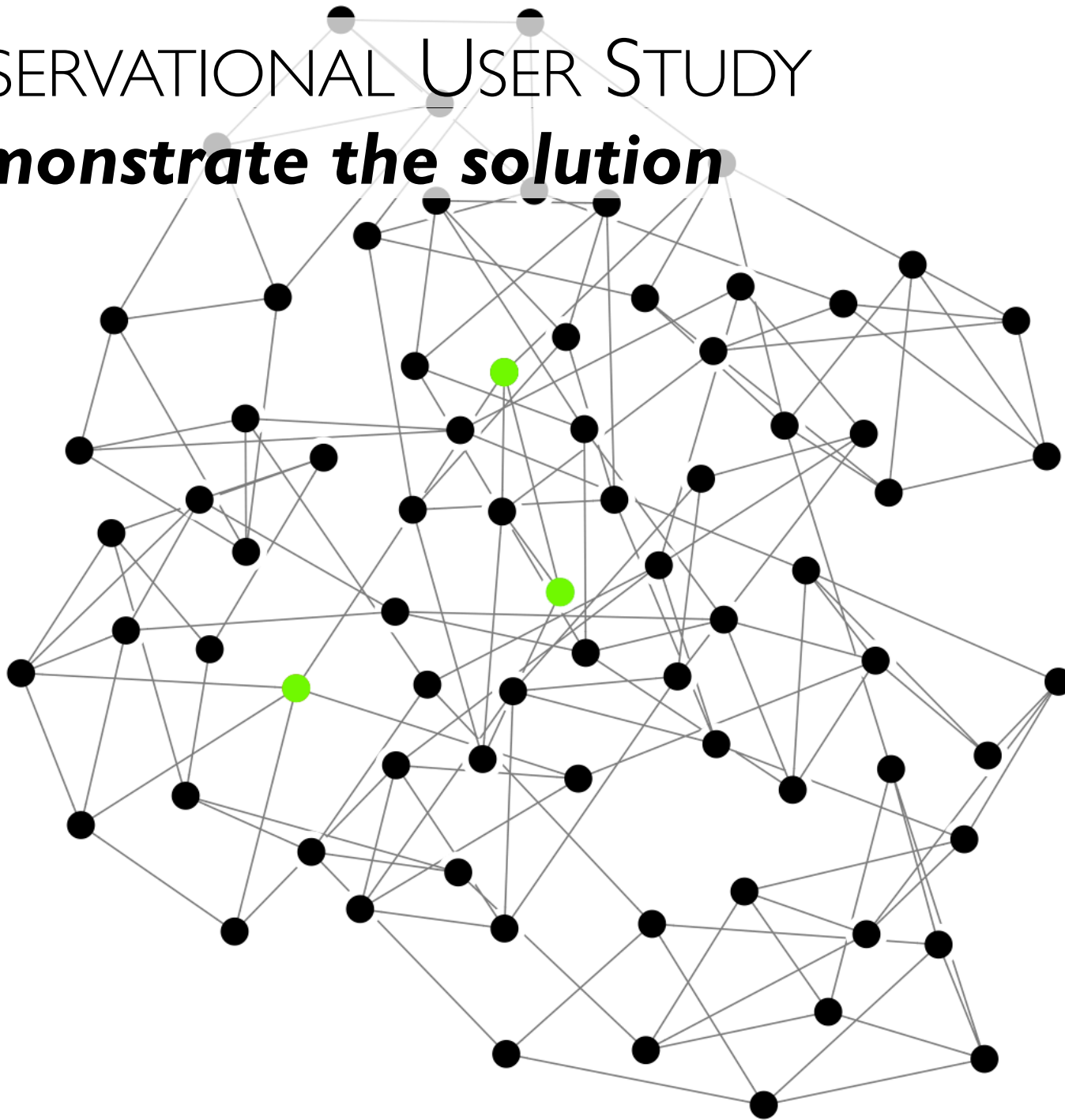
OBSERVATIONAL USER STUDY

Searching for the solution



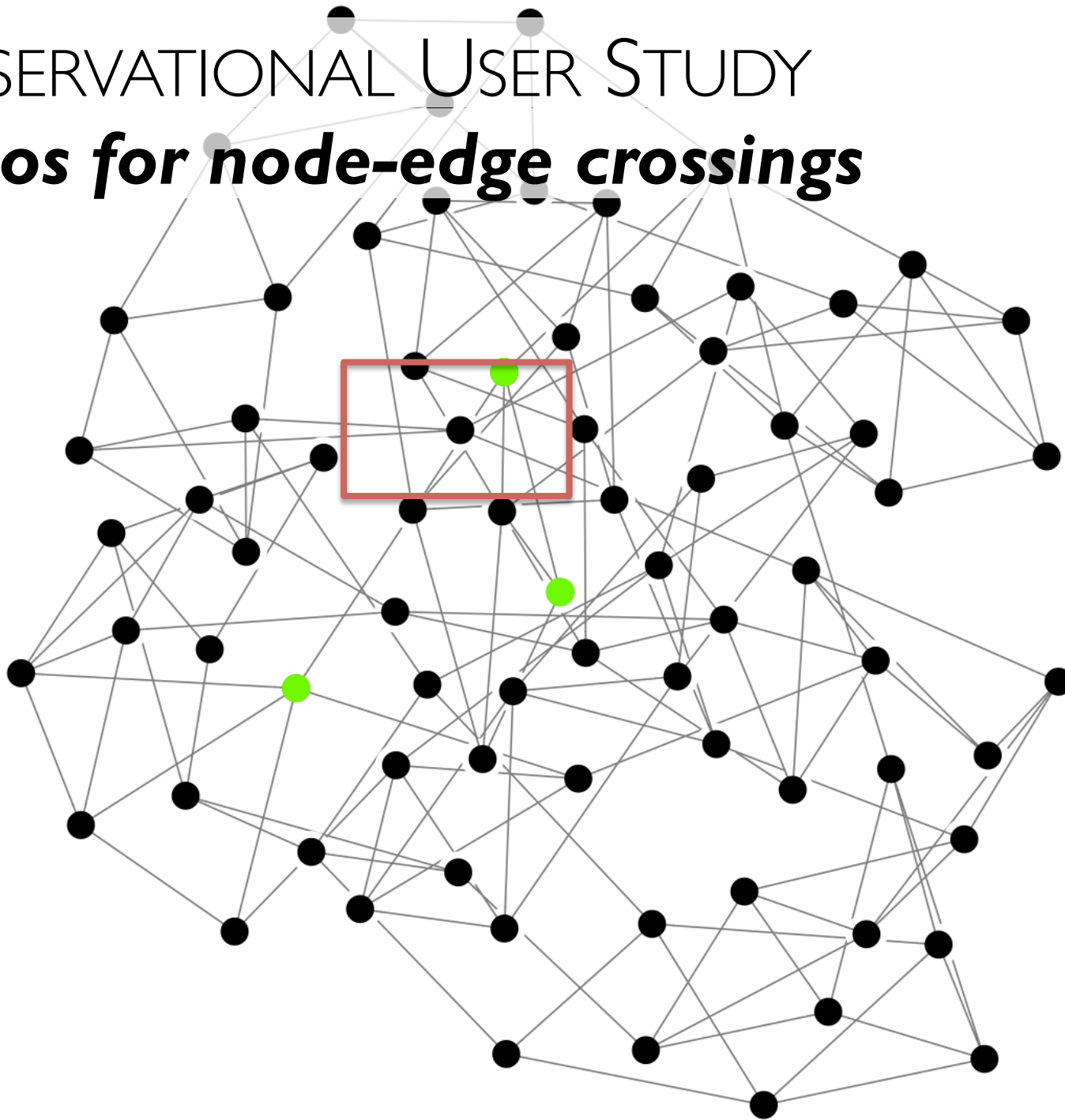
OBSERVATIONAL USER STUDY

Demonstrate the solution



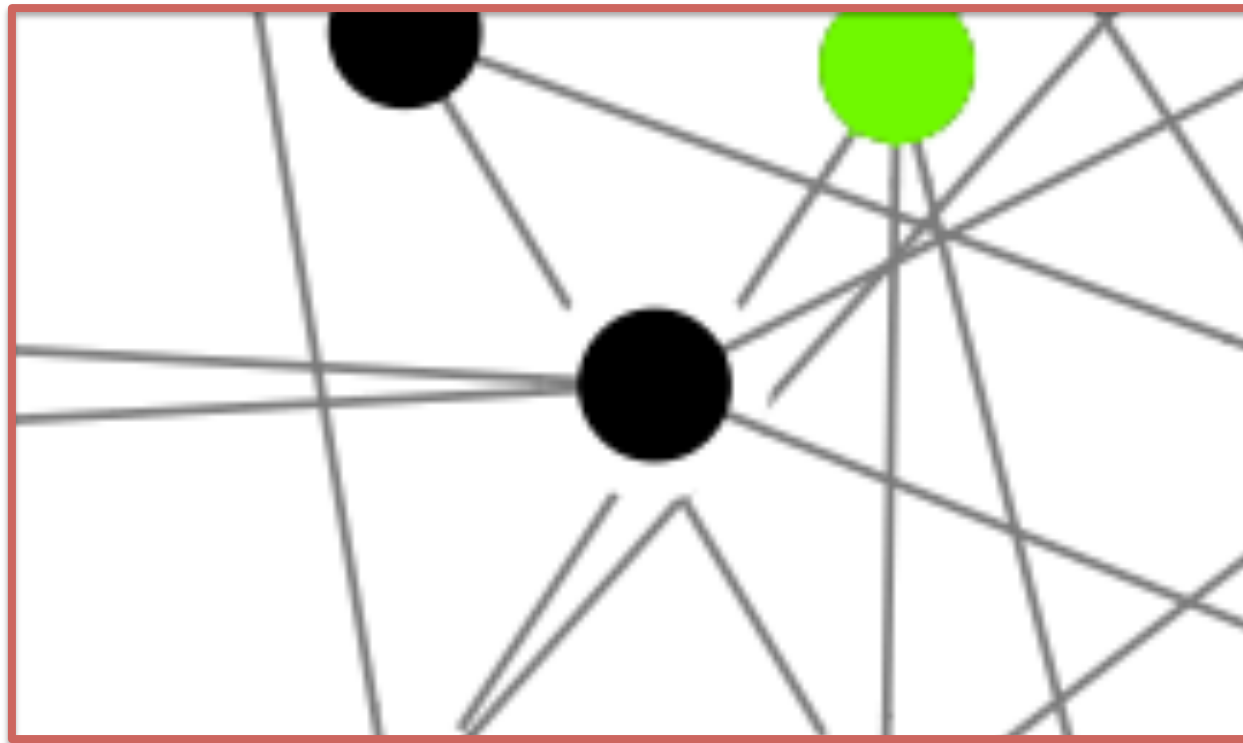
OBSERVATIONAL USER STUDY

Halos for node-edge crossings



OBSERVATIONAL USER STUDY

Halos for node-edge crossings



OBSERVATIONAL USER STUDY

Collected Data

- Primary Data
 - Sequences of *node hovers* along paths for each trial
 - Response time to complete trial
 - Error rate (correct/incorrect solution path)

ANALYSIS

Approach

Split into three parts:

- (1) Qualitative Analysis of Path Tracing Behaviours
- (2) Developing a Predictive Search Set Model
- (3) Multiple Regression Analysis Comparing Factors on Search Set Other Levels

QUALITATIVE ANALYSIS OF PATH TRACING BEHAVIOURS

Approach, Method, Key Results, Selected Path Tracing Behaviours

QUALITATIVE ANALYSIS

Approach

Addresses first two questions:

(Q1) can we identify distinct path tracing behaviours?

(Q2) how common are these behaviours?

QUALITATIVE ANALYSIS

Method

To support this analysis, we developed a series of visualizations to explore the **node hover** data:

- (1) Preliminary analysis of overlap of all nodes hovered per trial
- (2) Qualitative coding of paths (sequences of nodes)

QUALITATIVE ANALYSIS

Method

To support this analysis, we developed a series of visualizations to explore the **node hover** data:

- (1) Preliminary analysis of overlap of all nodes hovered per trial
- (2) Qualitative coding of paths (sequences of nodes)

QUALITATIVE ANALYSIS

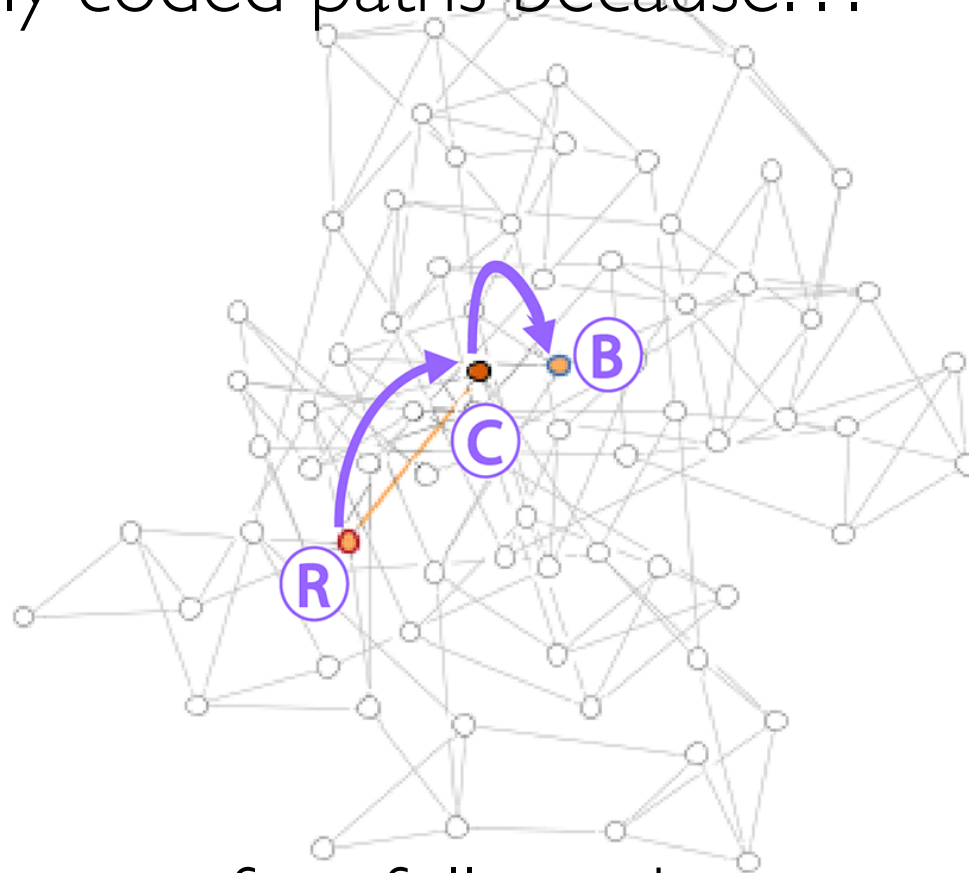
Method

- Manually coded paths because...

QUALITATIVE ANALYSIS

Method

- Manually coded paths because...

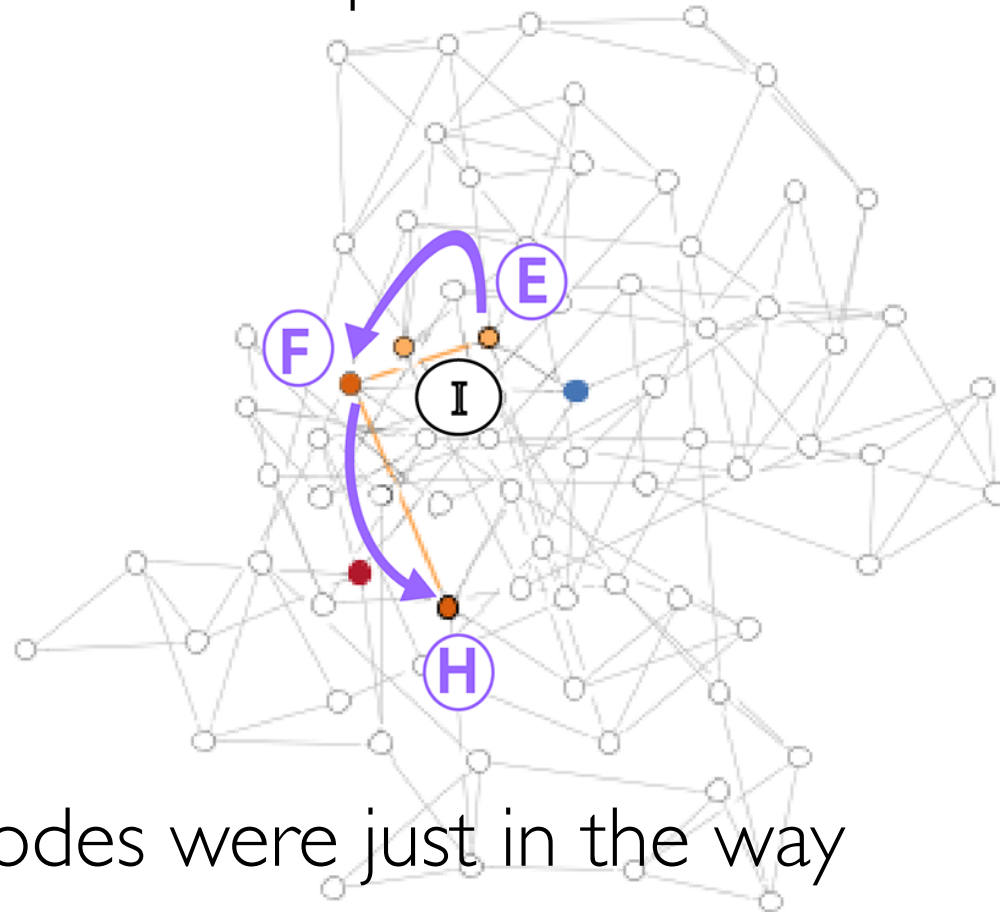


...participants often followed apparent paths

QUALITATIVE ANALYSIS

Method

- Manually identified paths because...



... some nodes were just in the way

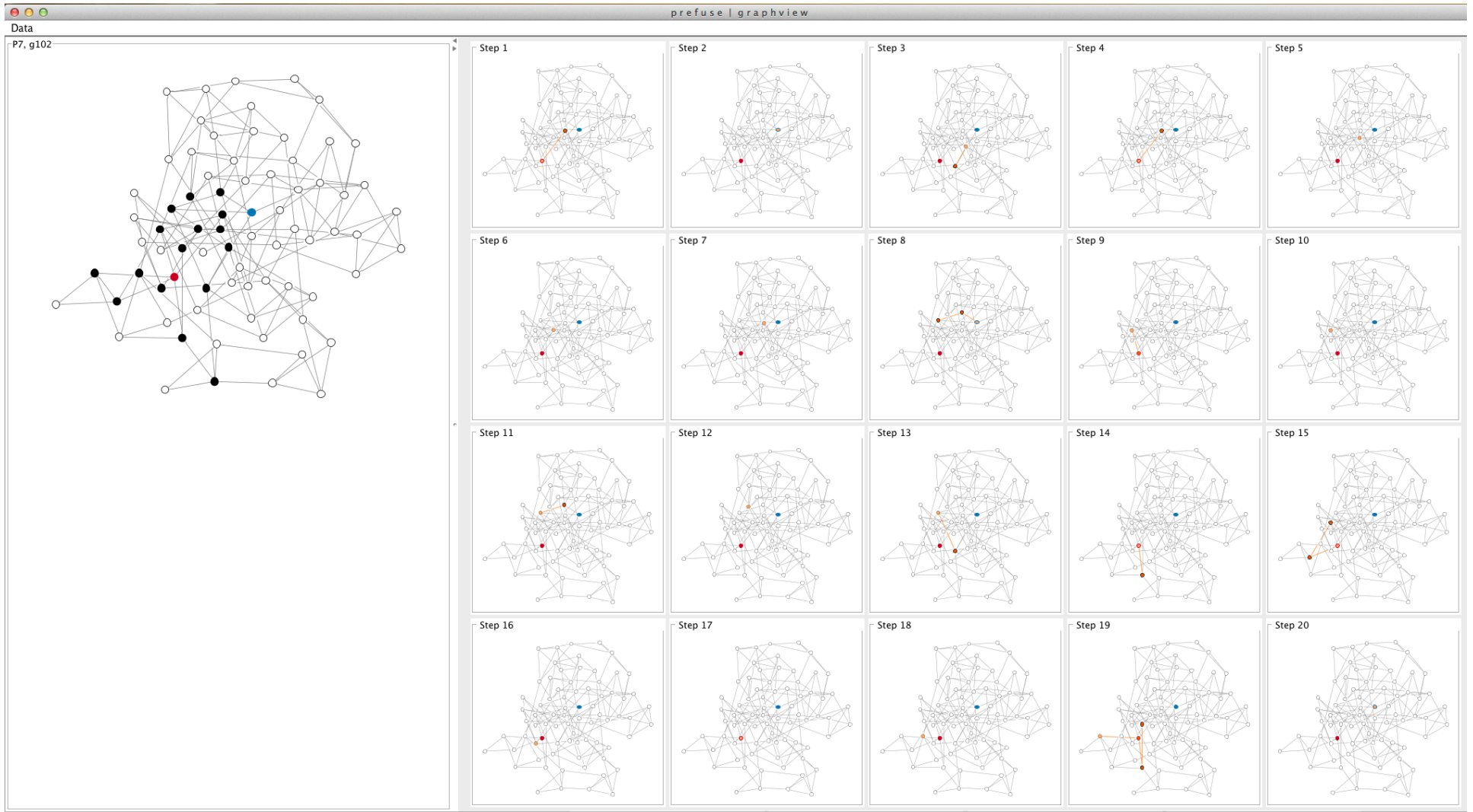
QUALITATIVE ANALYSIS

Method

- 24 study graphs analyzed (training set)
 - 12 participant trials per graph
 - For a total of 288 trials coded
 - Other 120 graphs reserved as validation set
- One investigator performed this coding solo
 - Some automatic highlighting of paths provided

QUALITATIVE ANALYSIS

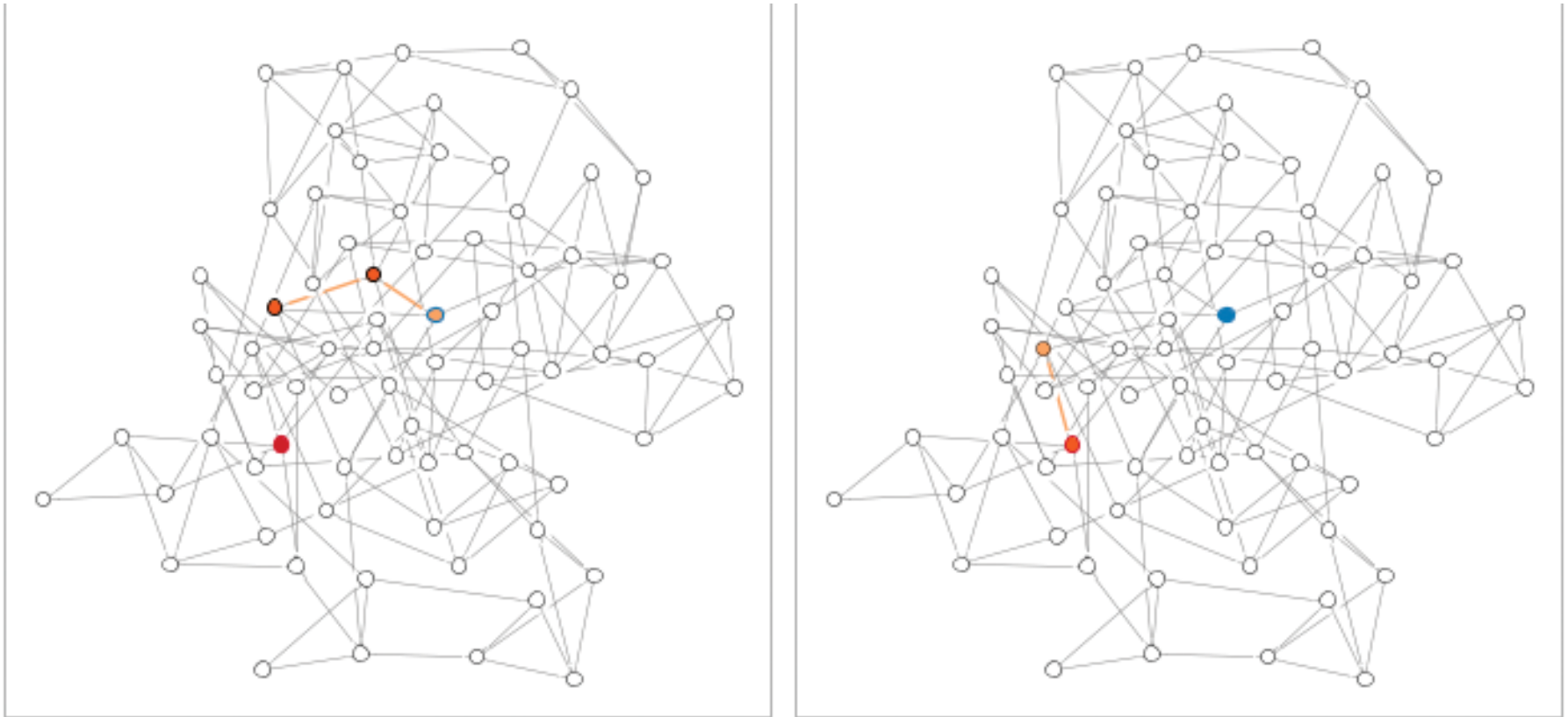
Screenshot of Visualization for Coding



QUALITATIVE ANALYSIS

Method

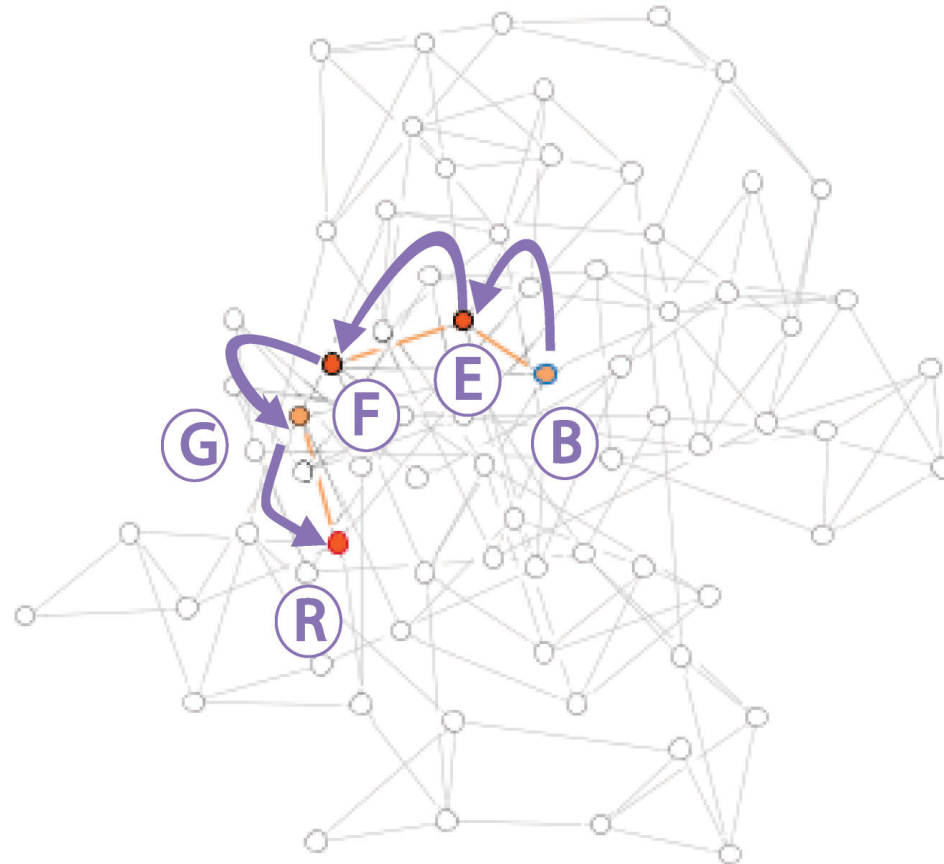
- Investigator looked at sequences of hovers . . .



QUALITATIVE ANALYSIS

Method

- And created textual descriptions of full paths



QUALITATIVE ANALYSIS

Method

- Many path dimensions recorded
 - **Anchor** nodes paths starts at
 - **Target** nodes paths go towards
 - Is a hop the **closest to geodesic**?
 - ...
- Also coded other interesting phenomenon
 - jumps between nodes
 - checks of node-edge crossings
 - ...

QUALITATIVE ANALYSIS

Key Results

- It is possible to identify distinct path tracing behaviours (Q I)
 - Investigator classified 96% of data examined with at least one code

QUALITATIVE ANALYSIS

Key Results

- Many common path tracing behaviours emerged from coding (Q2)
 - Use of both topological and apparent paths
 - Repeated exploration of paths
 - When participants stop following paths
 - Choice of nodes to search out from
 - Interactions of geodesic tendency with continuity
 - Prevalence of the geodesic tendency
 - Likely directions for the first hop in a path

QUALITATIVE ANALYSIS

Key Results

- Many common path tracing behaviours emerged from coding (Q2):
 - Use of both topological and apparent paths
 - Repeated exploration of paths
 - When participants stop following paths
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 - Interactions of geodesic tendency with continuity
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SELECTED PATH TRACING BEHAVIOURS

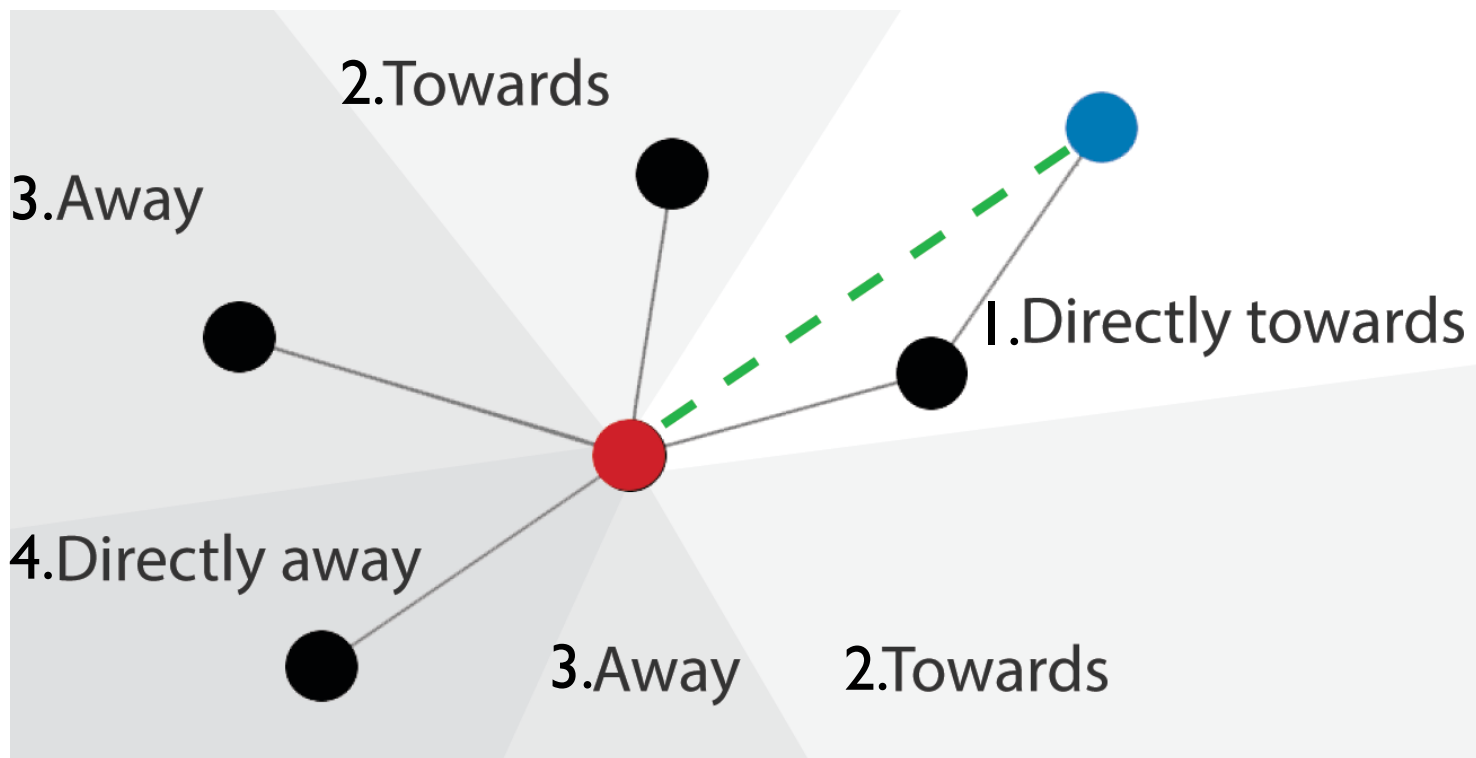
Prevalence of Geodesic Tendency

- Participants often followed closest to geodesic branches
 - for **all hops** in a path, 40% of the time
 - for **all but first or last hop**, 26% of the time
- Participants often aware of this behaviour
 - E.g., *“the [closest to geodesic] was more natural, it was harder to force myself to look away “[P6]”*

SELECTED PATH TRACING BEHAVIOURS

Likelihood of First Hop Directions

- We found we could organize the direction of first hop into groups of similar likelihoods



DEVELOPING A SEARCH SET MODEL

Approach, 3-Step Search Set Model, Validation

DEVELOPING A SEARCH SET MODEL

Approach

Addresses third question:

(Q3) can we predict a search set based on these behaviours?

- We designed a 3-step, predictive model based on the characterized behaviours

DEVELOPING A SEARCH SET MODEL

Approach

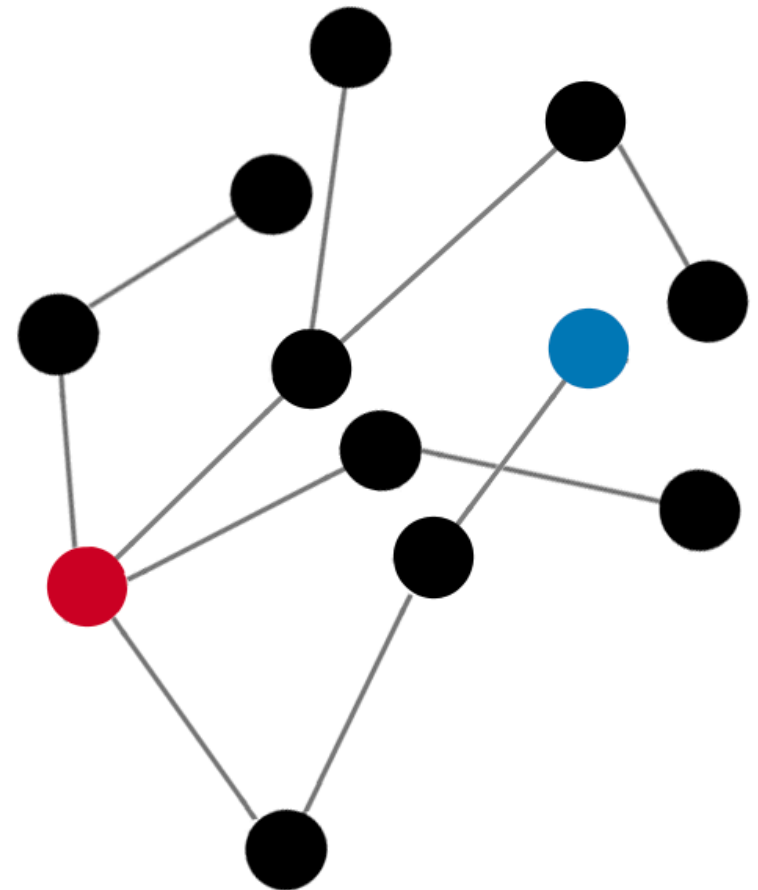
- Input: a connected network with a unique solution between start/end nodes
- Output: ordered batches of paths a user is likely to search
 - All paths in one batch similarly likely

3-STEP SEARCH SET MODEL

Step 1

Generate batch of likely first-hop candidates

- Starting with **directly towards**

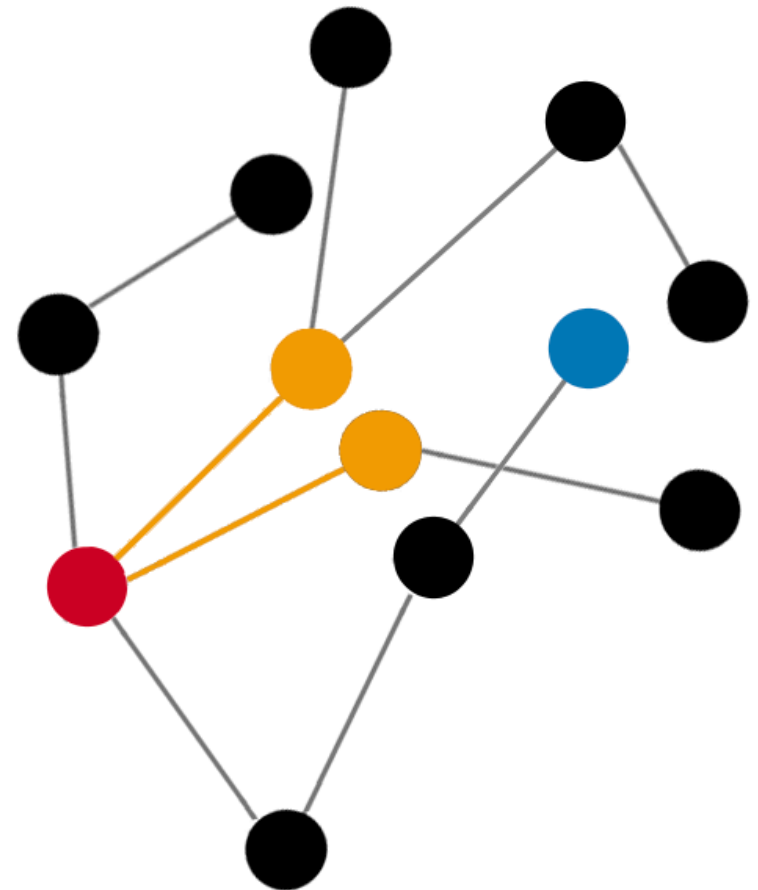


3-STEP SEARCH SET MODEL

Step 1

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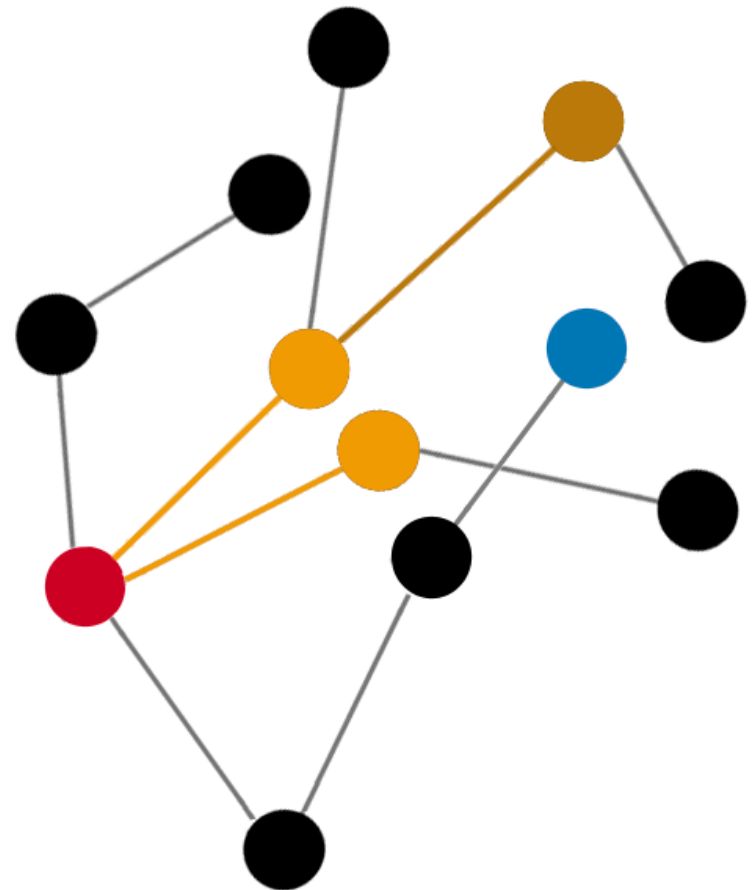


3-STEP SEARCH SET MODEL

Step 2

From each candidate, follow geodesic shortest branches

- Save path at each hop

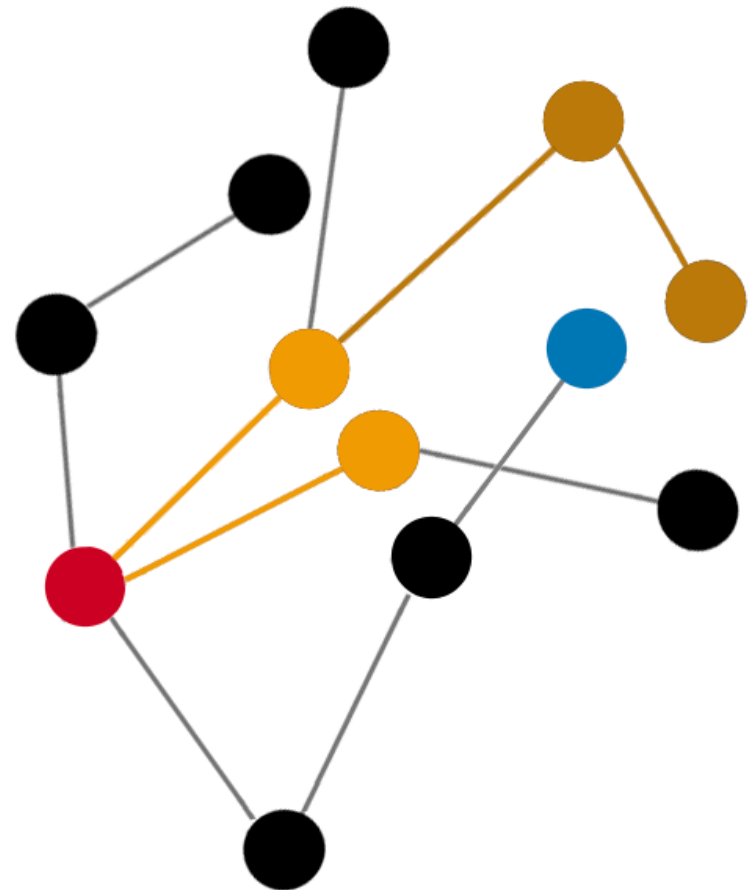


3-STEP SEARCH SET MODEL

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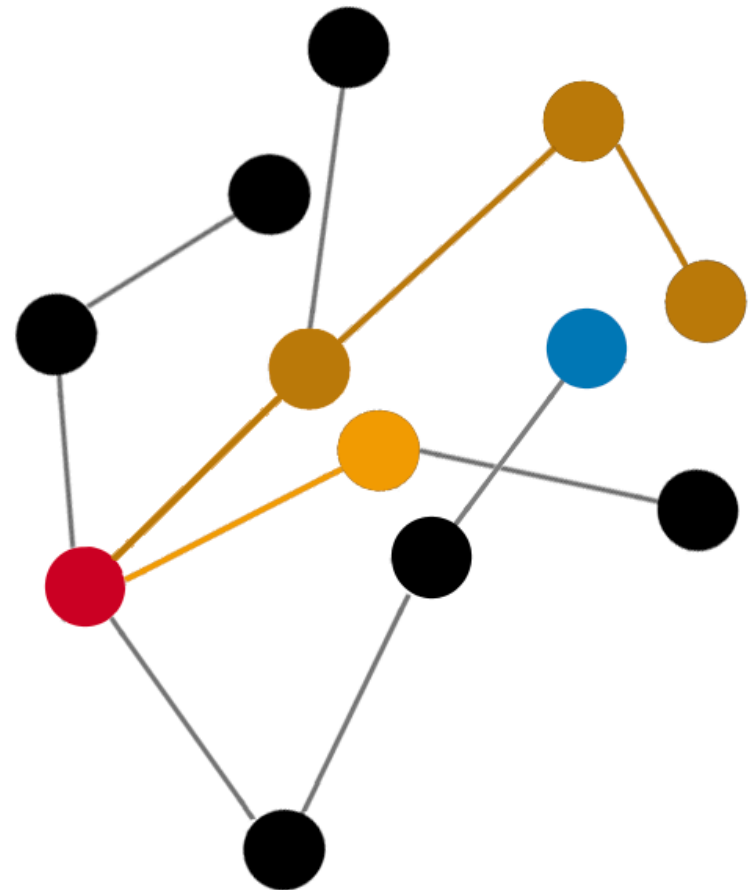


3-STEP SEARCH SET MODEL

Step 2

From each candidate, follow geodesic shortest branches

- Save path at each hop
- Go along path until stopping condition met

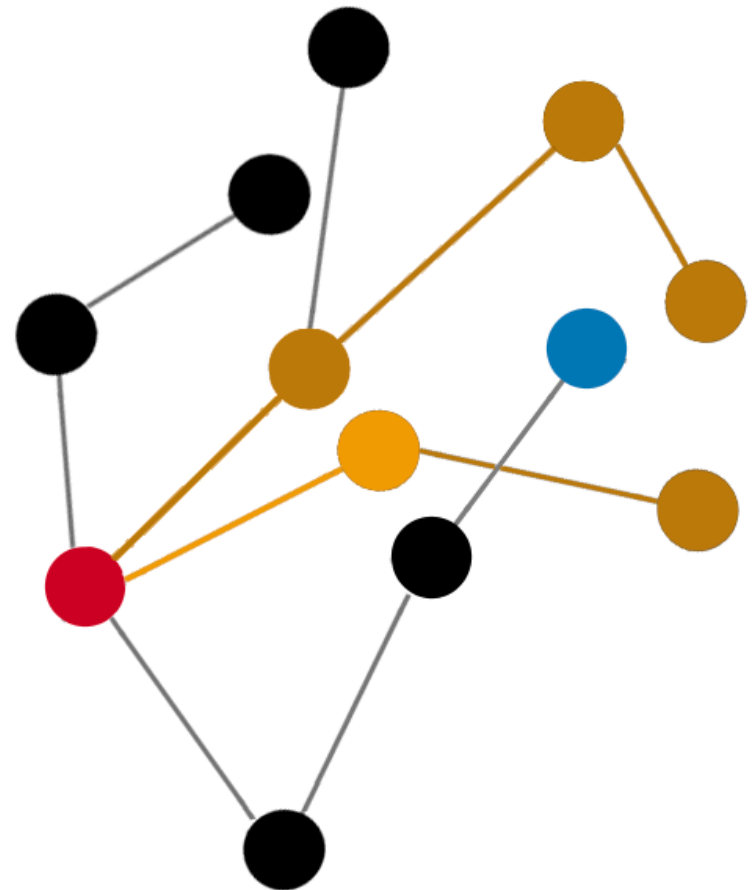


3-STEP SEARCH SET MODEL

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3-STEP SEARCH SET MODEL

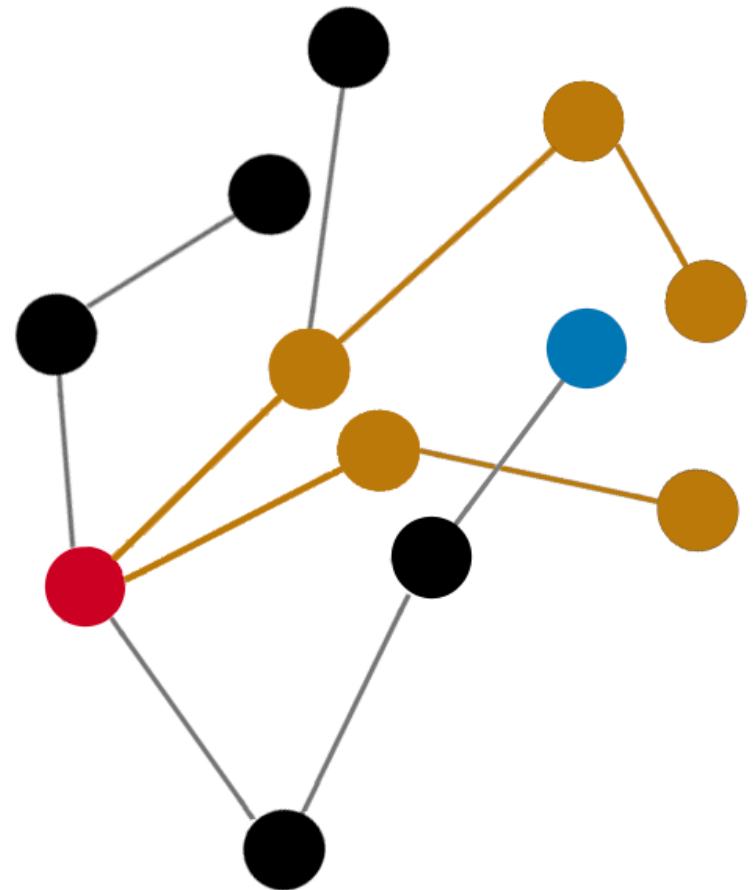
Step 2

From each candidate, follow geodesic shortest branches

- Save path at each hop
- Go along path until stopping condition met

End of step 2:

- Batch of equally likely paths

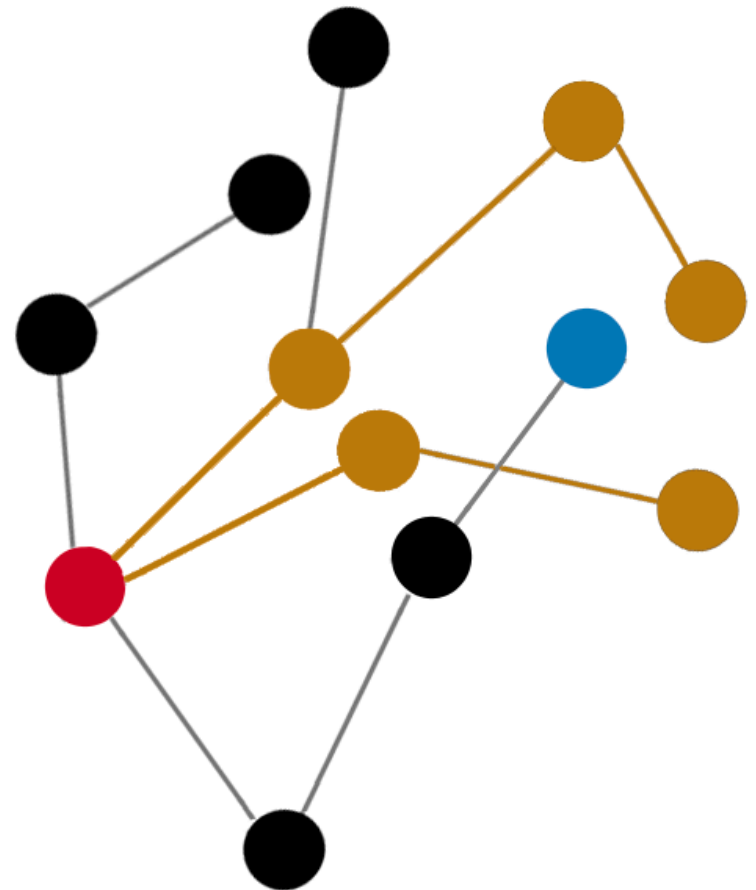


3-STEP SEARCH SET MODEL

Step 3

Does batch contains answer?

- If not: return to step 1

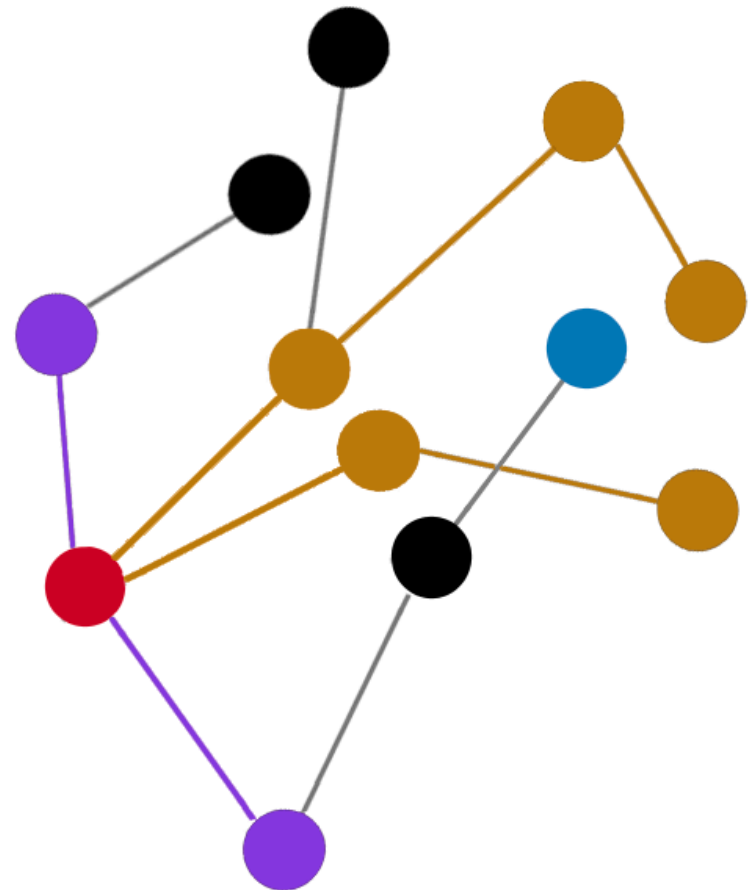


3-STEP SEARCH SET MODEL

Repeat Step 1

Generate batch of next most likely first-hop candidates

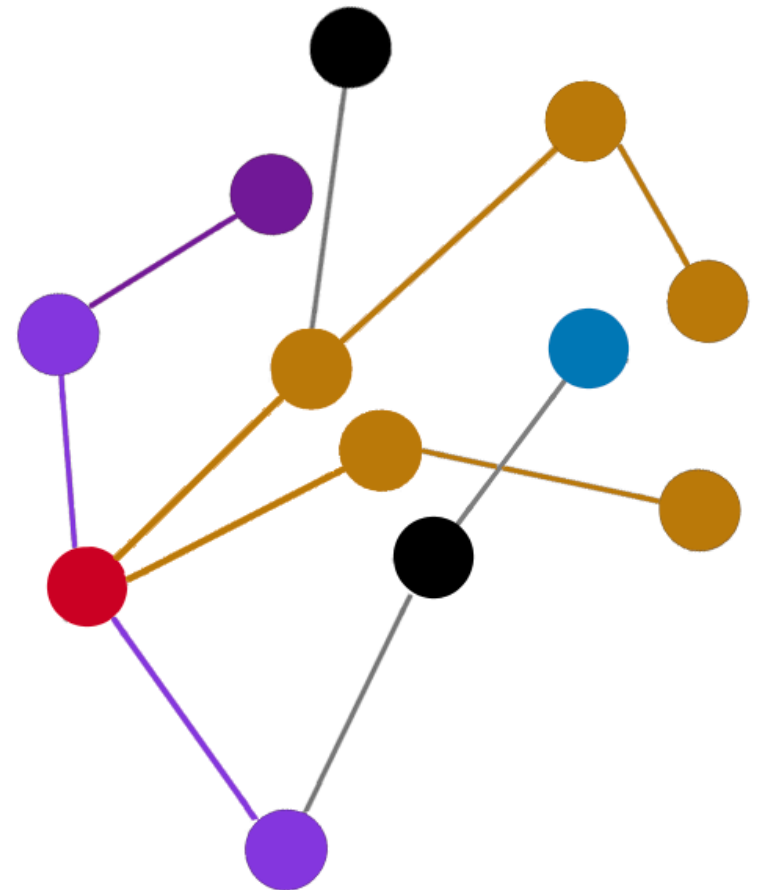
- Towards group



3-STEP SEARCH SET MODEL

Repeat Step 2

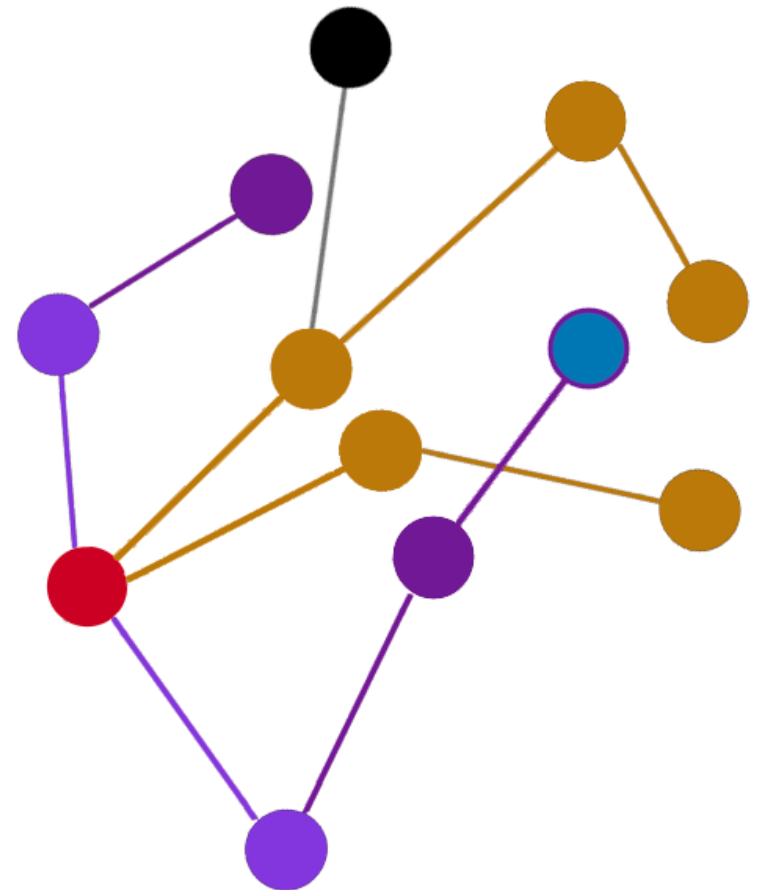
From each candidate, follow geodesic shortest branches



3-STEP SEARCH SET MODEL

Repeat Step 2

From each candidate, follow geodesic shortest branches



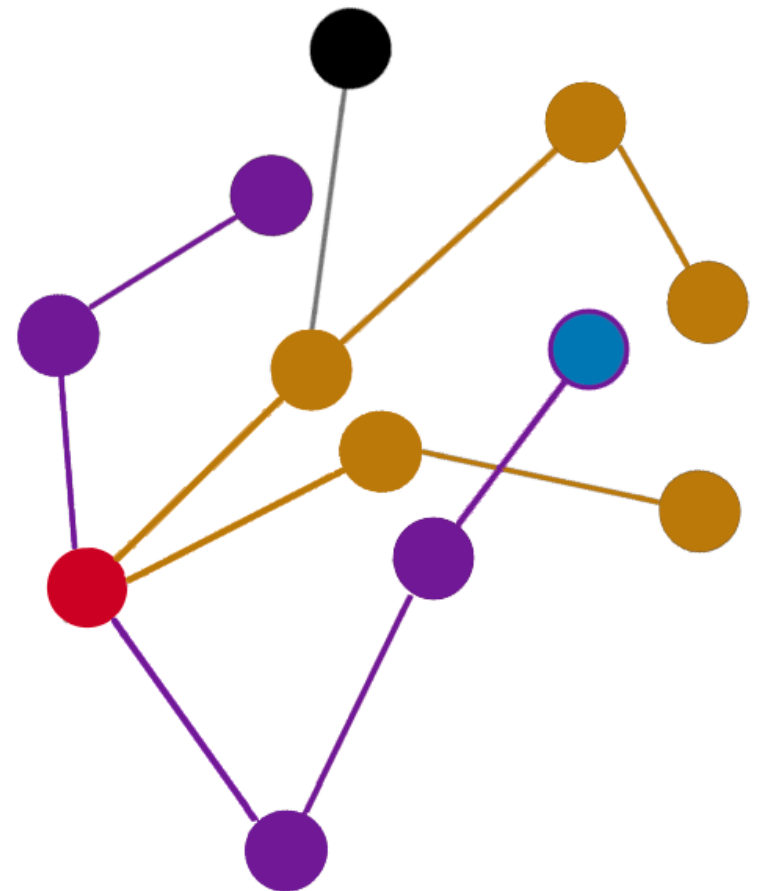
3-STEP SEARCH SET MODEL

Repeat Step 2

From each candidate, follow geodesic shortest branches

End of step 2:

- Next batch of equally likely paths

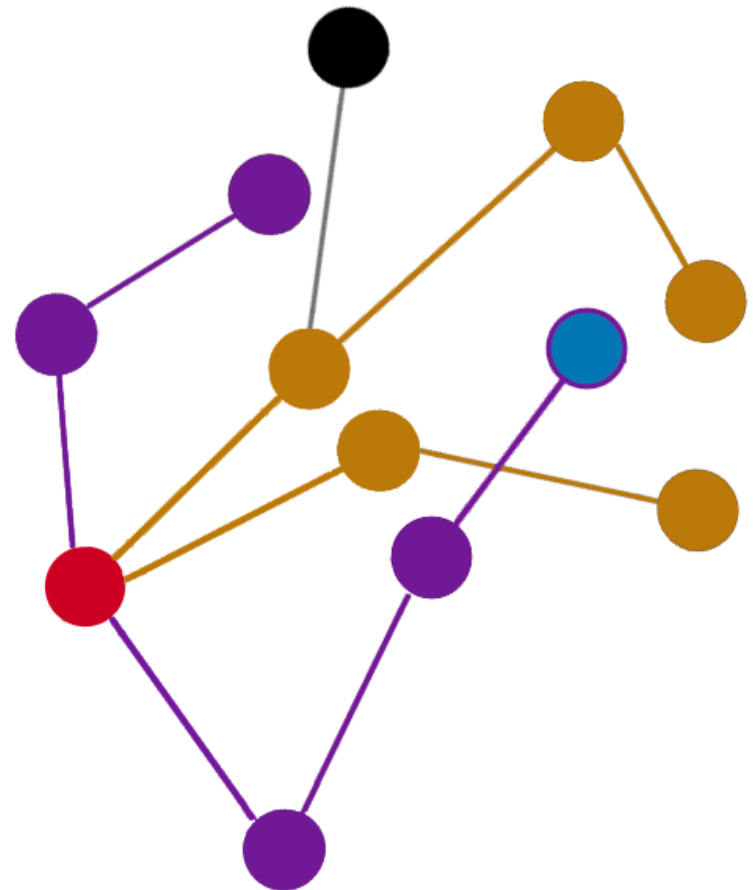


3-STEP SEARCH SET MODEL

Repeat Step 3

Does batch contains answer?

- Yup! So stop



DEVELOPING A PREDICTIVE MODEL

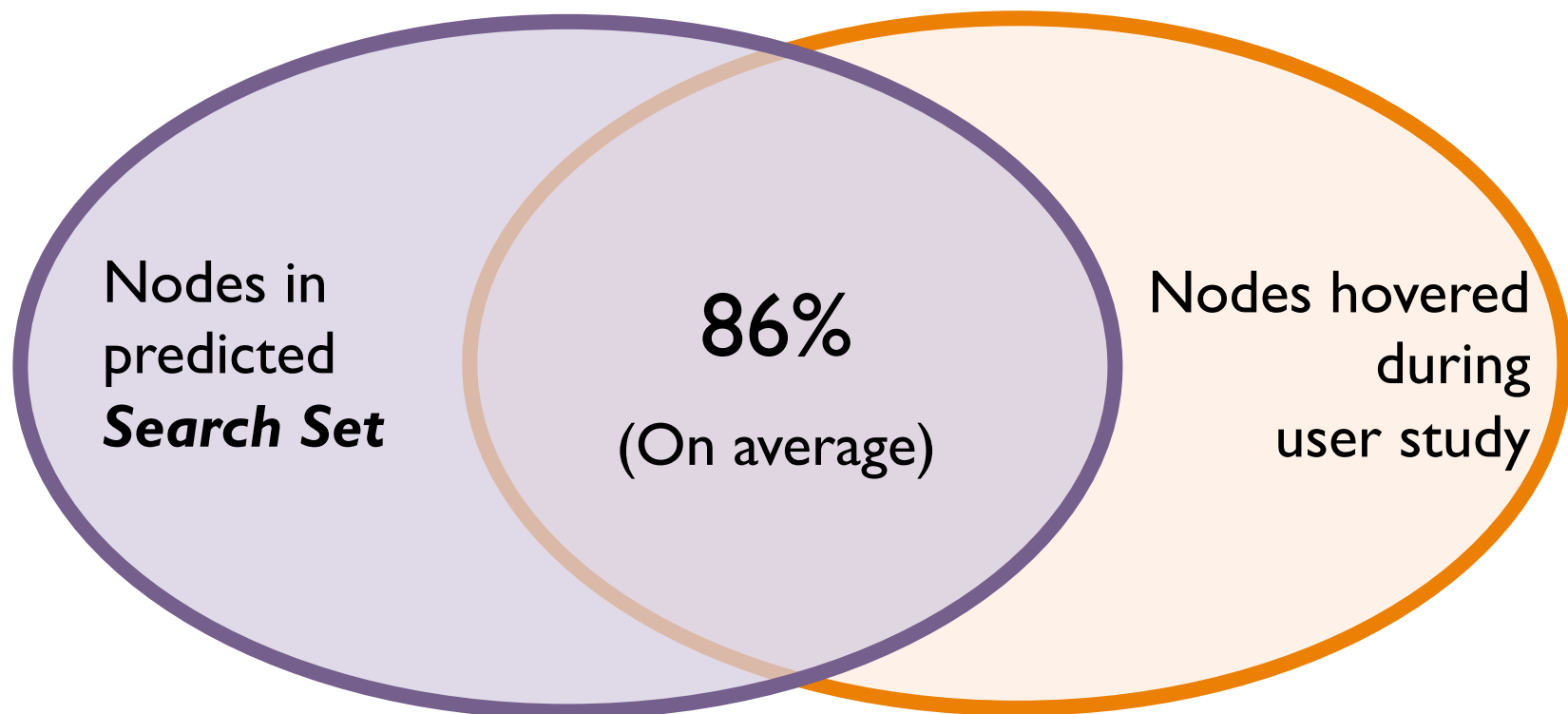
Algorithmic Implementation

- Implemented algorithm to run on actual graphs from study
 - Iterated on assigned parameters for angles, etc.
 - Used training set graphs to test model fit to data

DEVELOPING A PREDICTIVE MODEL

Validation: Key Results

- Yes, can predict search set based on observed path tracing behaviours (Q3)



DEVELOPING A PREDICTIVE MODEL

Validation (2): Key Results

- Yes, measuring factors on the search set does seem to be effective (Preliminary Q4).

MULTIPLE REGRESSION ANALYSIS

Approach, Related Work, Method, Key Results

MULTIPLE REGRESSION ANALYSIS

Approach

Addresses fourth question:

(Q4) how much improvement from measuring factors on search set?

- Preliminary validation of one possible application of search set

MULTIPLE REGRESSION ANALYSIS

Factor Levels

- Only one study has compared levels of factors
 - Edge-edge crossings at global vs. solution-path level
[Ware et al., 2002]
- We compared search set factors to previously studied factors at:
 - global levels
 - solution path levels

MULTIPLE REGRESSION ANALYSIS

Regression vs. Significance Testing

- Most previous work uses significance testing to determine a factor is important
- Multiple regression accounts for relative importance and overlap in what factors predict
- Only two studies have used regression to compare relative importance of factors

[Ware et al., 2002] [Huang & Huang, 2011]

MULTIPLE REGRESSION ANALYSIS

Method

- 9 factors total:
 - Global node-edge crossings
 - Global edge-edge crossings
 - Search set node-edge crossings
 - Search set: edge-edge crossings
 - Solution path node-edge crossings
 - Solution path edge-edge crossings
 - Solution path length (# of hops)
 - Solution path continuity (bendiness)
 - Solution path branches (# of edges on each node)

MULTIPLE REGRESSION ANALYSIS

Method

- Previously Studied:
 - Global node-edge crossings
 - Global edge-edge crossings**
 - Search set node-edge crossings
 - Search set: edge-edge crossings
 - Solution path node-edge crossings
 - Solution path edge-edge crossings**
 - Solution path length (# of hops)**
 - Solution path continuity (bendiness)**
 - Solution path branches (# of edges on each node)**

MULTIPLE REGRESSION ANALYSIS

Method

- Focus of today on:
 - Global node-edge crossings
 - Global edge-edge crossings
 - Search set node-edge crossings
 - Search set: edge-edge crossings**
 - Solution path node-edge crossings
 - Solution path edge-edge crossings
 - Solution path length (# of hops)
 - Solution path continuity (bendiness)
 - Solution path branches (# of edges on each node)

MULTIPLE REGRESSION ANALYSIS

Method

- Data sample
 - 120 graphs (reserved validation set)
 - Factors measured on each graph
- Dependent variables:
 - Average response time
 - Errors per graph (0 – 12)

MULTIPLE REGRESSION ANALYSIS

Key Results

- Individual effects of factors
 - Replicated PW showing **solution path** factors strongly correlated with **response time**
 - New result: same effect for **error**

MULTIPLE REGRESSION ANALYSIS

Key Results

- Individual effects of factors
 - Replicated PW showing solution path factors strongly correlated with response time
 - New result: same effect for error
 - **Search set edge-edge** crossings strongly correlated with **response time** and **error**

MULTIPLE REGRESSION ANALYSIS

Key Results

- Individual effects of factors
 - Replicated PW showing solution path factors strongly correlated with response time
 - New result: same effect for error
 - Search set edge-edge crossings strongly correlated with response time and error
 - **Global factors** not correlated with **response time** or **error**
 - Contrary to some previous work

MULTIPLE REGRESSION ANALYSIS

Key Results

- Search set edge-edge crossings had small effect over previous work:
 - Response time: additional 1.8% variance
 - Error: additional 4.2% variance
- ... On top of what all solution path factors explained

MULTIPLE REGRESSION ANALYSIS

Key Results

- Search set edge-edge crossings had small effect over previous work:
 - Response time: additional 1.8% variance
 - Error: additional 4.2% variance
 - ... On top of what all solution path factors explained
- **Search set edge-edge crossings** improved efficiency
 - Fewer total variables needed to account for same variance

MULTIPLE REGRESSION ANALYSIS

Key Results

- Final regression models:
 - 79% of variance in response time explained by
 1. Solution path length
 2. Solution path continuity
 3. Search set edge-edge crossings
 - 60% of variance in error explained by
 1. Search set edge-edge crossings
 2. Solution path continuity

CONCLUSION

Contributions Recap, Discussion & Future Work

THESIS CONTRIBUTIONS

Recap

- (1) The concept of a search set in path tracing
- (2) A detailed characterization of path tracing behaviours
- (3) A predictive model of a search set
- (4) A multiple regression analysis using search set to measure factors that affect graph readability

DISCUSSION & FUTURE WORK

Behaviour Characterization

- Characterization of path tracing behaviours extends beyond geodesic tendency [Huang et al. 2011]
 - We provide a complete model from start to finish
- Coding limited by human judgment, only one coder
 - Future analysis could address with additional coders, computational approaches

DISCUSSION & FUTURE WORK

Predictive Behavioural Model

- Model represents a good first step, but not perfect
- Future work should improve on search set model breadth, completeness, and accuracy

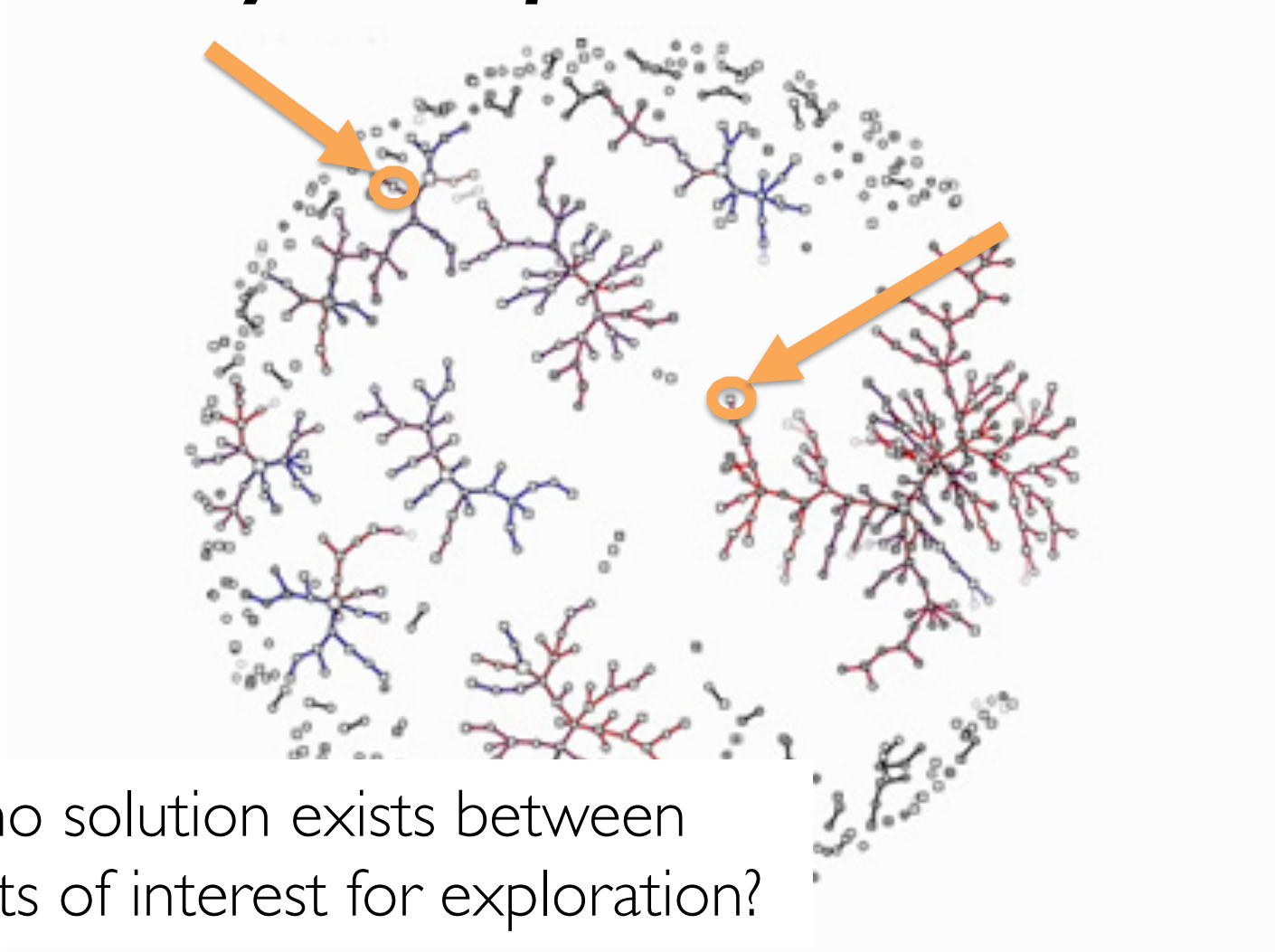
DISCUSSION & FUTURE WORK

Measuring Search Set Factors

- Our regression analysis provides
 - Validation of the model/concept
 - An example of how the search set could be used
- Future work could examine
 - If more accurate model provides further improvement
 - Effects of other factors on the search set
- Showed small gains over solution path
 - Search set factors may be more broadly applicable
 - Although more expensive

DISCUSSION & FUTURE WORK

Applicability Example



What if no solution exists between two points of interest for exploration?

DISCUSSION & FUTURE WORK

Usefulness of Search Set Concept

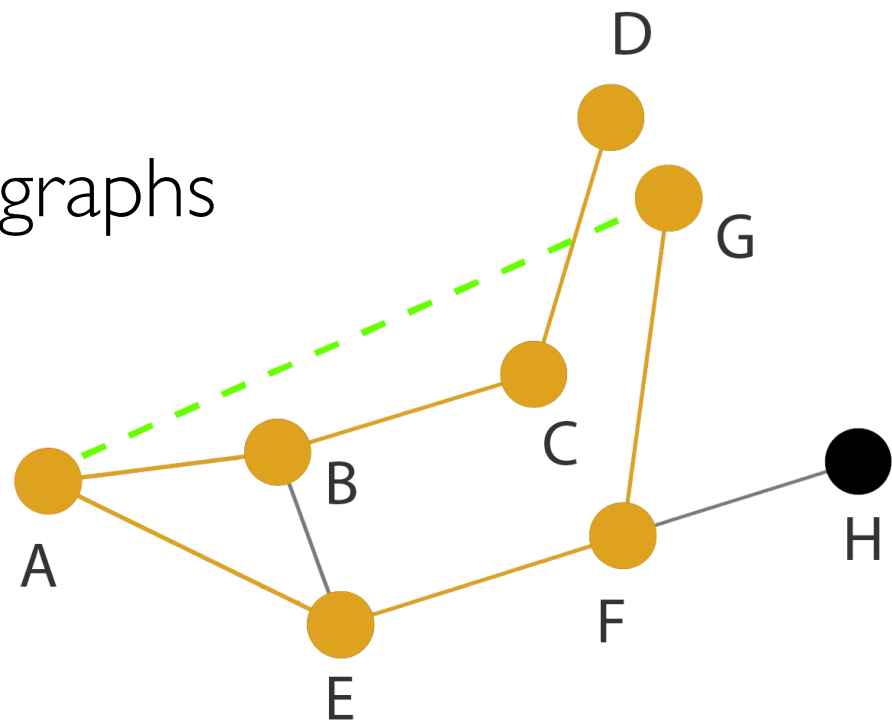
- Analysis of the subset of a graph most relevant to the task can be very informative
- For example
 - previous work graph sizes might explain inconsistent findings on global edge-edge crossings

DISCUSSION & FUTURE WORK

Usefulness of Search Set Concept

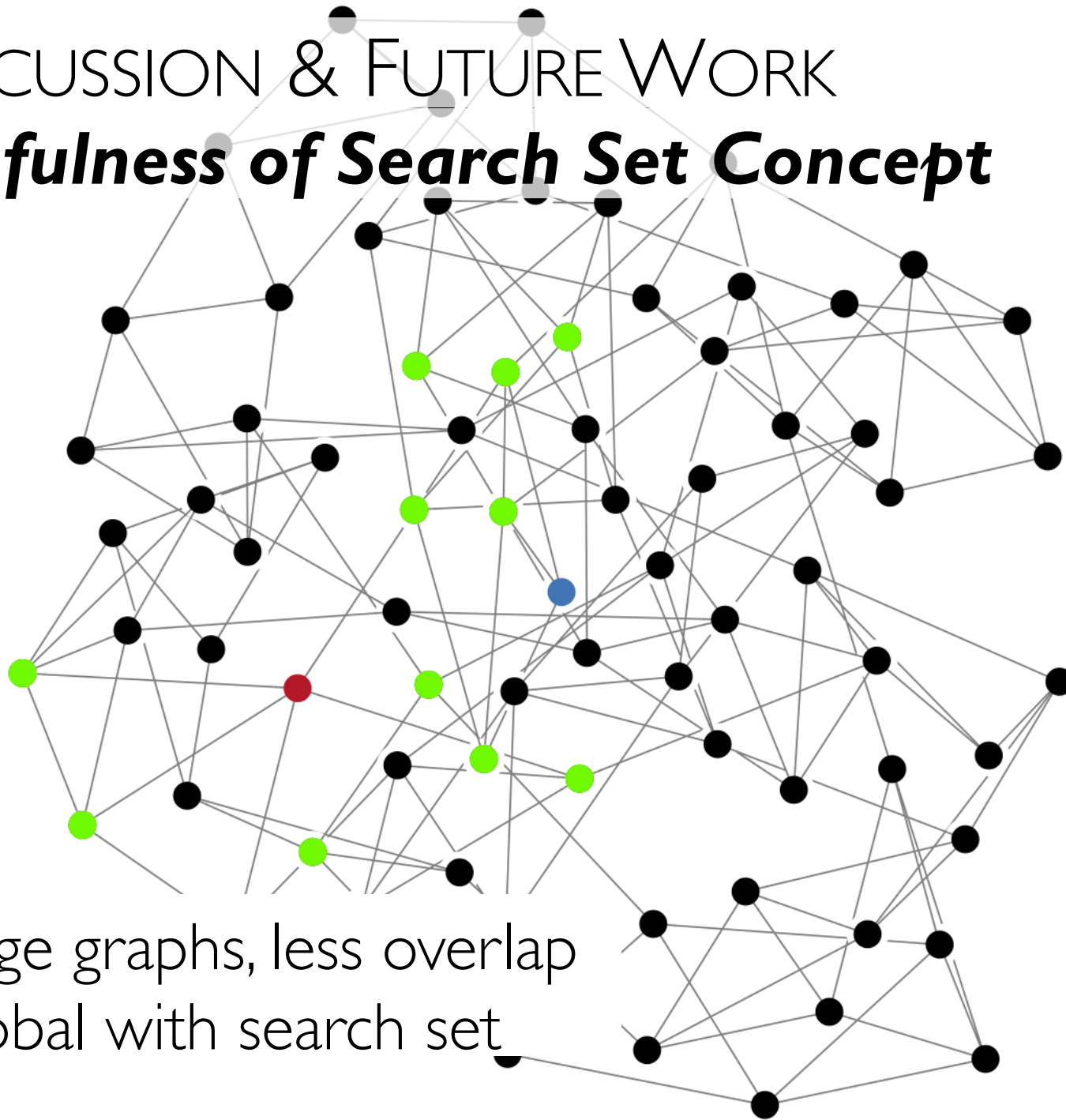
Most studies used small graphs

- where search set often overlaps with global



DISCUSSION & FUTURE WORK

Usefulness of Search Set Concept



In large graphs, less overlap
of global with search set

DISCUSSION & FUTURE WORK

Usefulness of Search Set Concept

- Future work should explore use of search set for other applications:
 - Design of new interaction techniques
 - New automatic graph layouts that make subtle changes to preserve consistency

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QUESTIONS?

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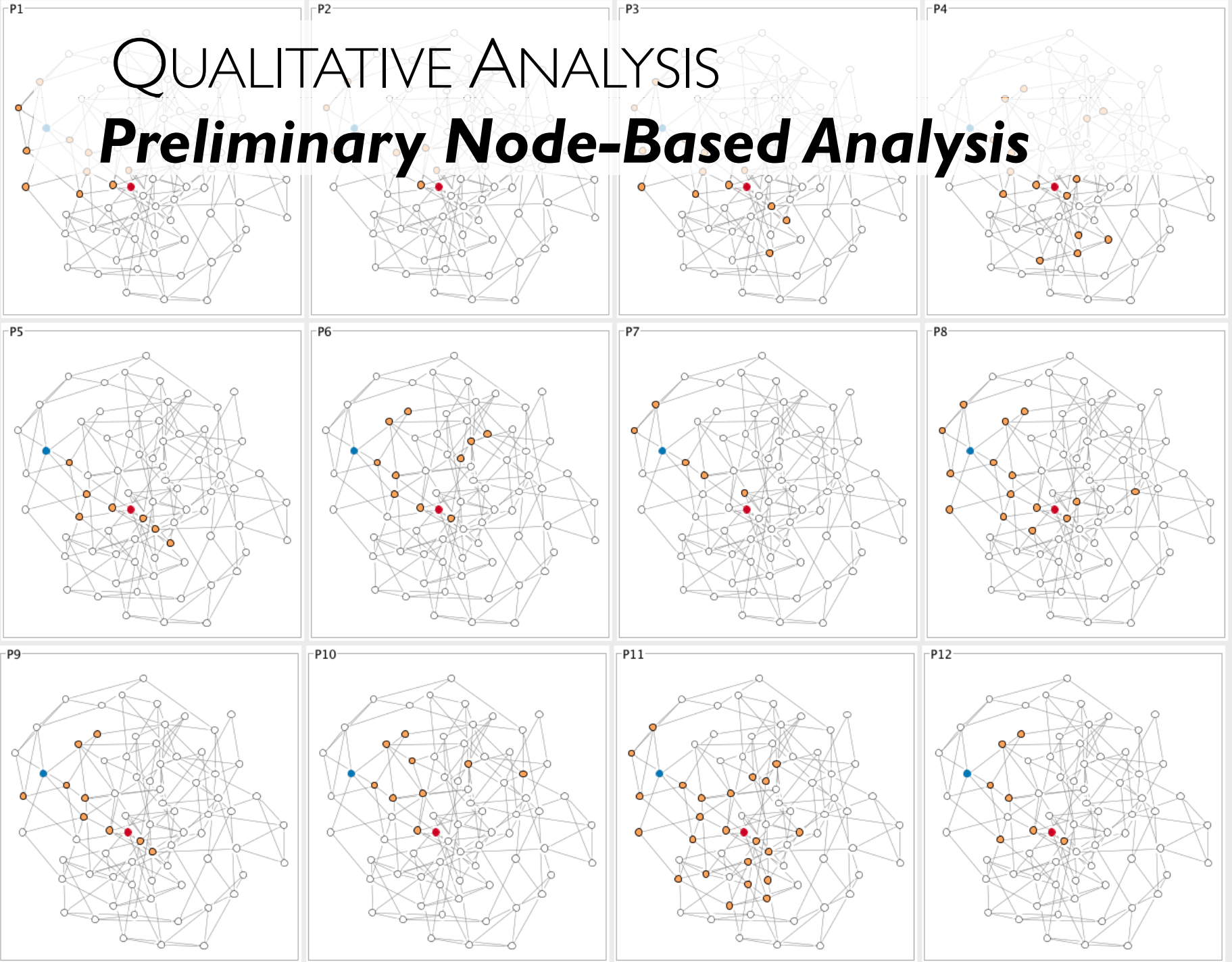
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QUALITATIVE ANALYSIS

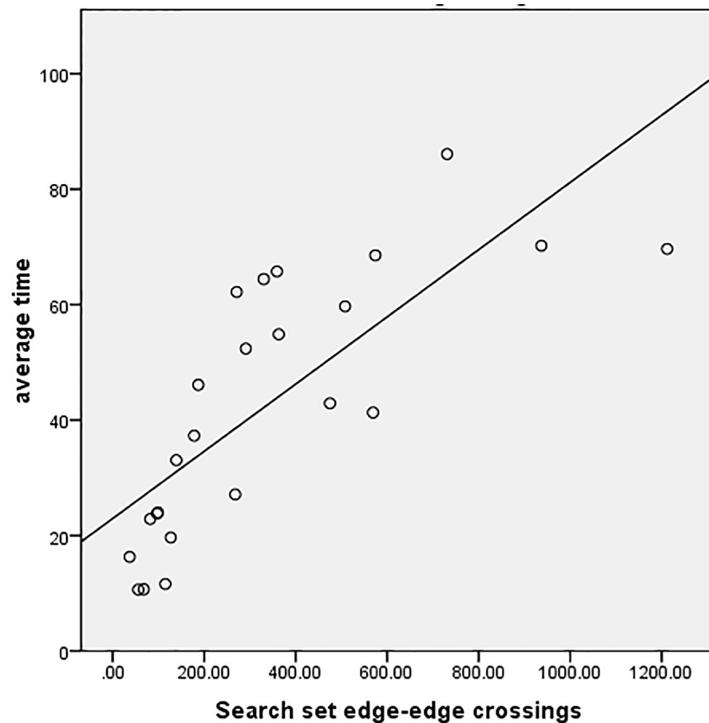
Preliminary Node-Based Analysis



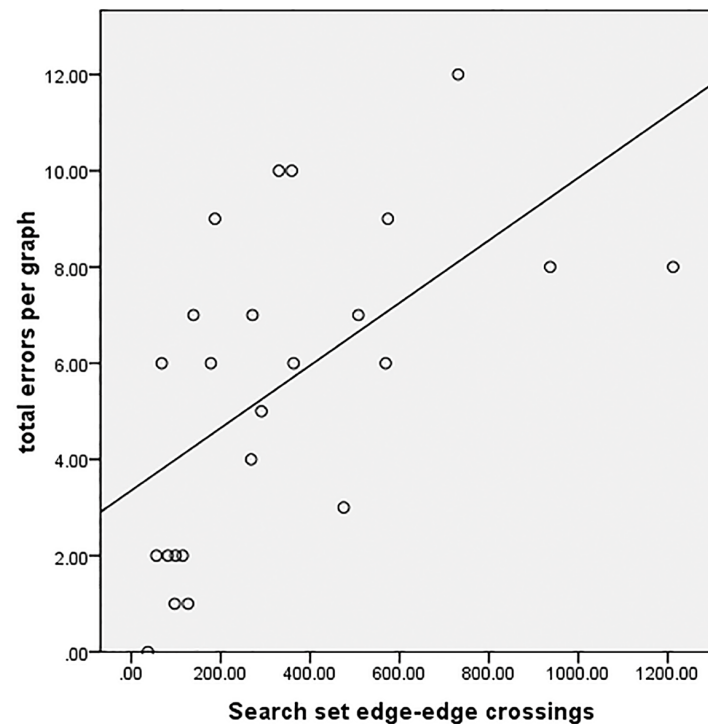
DEVELOPING A PREDICTIVE MODEL

Validation (2): Key Results

- We found strong positive correlations between search set edge-edge crossings and:



(1) Response time ($r = 0.772$)



(2) Total errors ($r = 0.582$)