Bayesian Information Gain for Guiding Multiscale Navigation

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10.10.2017

Multiscale Navigation
Multiscale Navigation

Maps

Documents

High-resolution Images

Infinite Zooming
Multiscale Navigation

Overview + Detail

Focus + Context

Treemap

Hyperbolic Tree
In Standard Multiscale Navigation

The user is in full control. The computer executes the user input.
In Standard Multiscale Navigation

View

Input
Standard Multiscale Navigation can be frustrating and inefficient...
How to improve multiscale navigation by having the computer play a more active role?

#partnership
Points of Interest

View

Information.

Input

Intention
We introduce **BIGnav**, a guided navigation technique that uses priori knowledge of the information space and progressively acquired information of the user’s intention.
BIGnav:
Bayesian Information Gain Navigation
The Scientist
The scientist optimizes the choice of the experiment by maximizing the expected utility.
Choose the view that maximizes the expected information gain from the next user input.
BIGnav: Bayesian Information Gain Navigation

\[ P(\Theta = \theta_i) \]

\[ \Theta \]

\[ \theta_3 \]
BIIGNav: Bayesian Information Gain Navigation
BIGnav: Bayesian Information Gain Navigation

View $X = x$

$\theta_3$
BIGnav: Bayesian Information Gain Navigation

United States

Denver

Kansas City

Chicago

Philadelphia

New York
BIGnav:
Bayesian Information Gain Navigation

User Input $Y = y$
BIGnav: Bayesian Information Gain Navigation
BIGnav: Bayesian Information Gain Navigation

\[ P(Y = y | \Theta = \theta, X = x) \]

Interpret User Input

\[ P(\Theta = \theta_i) \]

User Input \( Y = y \)

View \( X = x \)
**BIGnav:**
Bayesian Information Gain Navigation

\[
\Pr(\rightarrow | \text{NYC is the intended target, currently see Denver}) = 95\%
\]

\[
\Pr(\leftarrow | \text{NYC is the intended target, currently see Denver}) = 5\%
\]
**BIGnav:**
Bayesian Information Gain Navigation

\[ P(\Theta = \theta | X = x, Y = y) \]

Update its knowledge

\[ P(\Theta = \theta_i) \]

User Input \( Y = y \)

View \( X = x \)

\( \theta_3 \)
BIGnav:
Bayesian Information Gain Navigation
**BIGnav:**
Bayesian Information Gain Navigation

\[ IG(\Theta \mid X = x, Y) = H(\Theta) - H(\Theta \mid X = x, Y) \]

Navigate to a new view that maximizes the expected information gain.

User Input \( Y = y \)

View \( X = x \)

\( \theta_3 \)
BIGnav: Bayesian Information Gain Navigation
BIGnav: Bayesian Information Gain Navigation

$$IG(\Theta|X = x, Y = y) = H(\Theta) - H(\Theta|X = x, Y = y)$$

Calculate the actual information gain

View $X = x$

$$P(\Theta = \theta_i)$$

User Input $Y = y$
BIGnav: Bayesian Information Gain Navigation
BI Gn nav in 1D

- User inputs: Go left, go right, zoom in
- Darker color indicates higher probability of the target $P(\Theta = \theta)$

$$P(Y = y | \Theta = \theta, X = x) = 0.9 \text{ or } 0.05$$
BIGnav in 1D

* User inputs: Go left, go right, zoom in
* Darker color indicates higher probability of the target $P(\Theta = \theta)$
**BIGnav in 2D**

* User inputs are discretized into 8 pan directions and 1 zoom-in region
BIGnav in 2D

* A calibration session to understand user behavior

$$P(\Theta = \theta \mid X = x, Y = y)$$

**Results:**

<table>
<thead>
<tr>
<th>Command</th>
<th>Main Region</th>
<th>Adjacent Regions</th>
<th>Other Regions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pan</td>
<td>90%</td>
<td>8%</td>
<td>2%</td>
</tr>
<tr>
<td>Zoom</td>
<td>95%</td>
<td>1.25%</td>
<td>3.75%</td>
</tr>
<tr>
<td>Click</td>
<td>100%</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
BIGnav in 2D
Experiments

- Full factorial within-participant design:
  - 16 Participant
  - x 2 Navigation Technique
  - x 5 Index of Difficulty x 6 Distribution
  - x 5 Replication

- Technique: BIGnav, STDnav

- Index of Difficulty: 10, 15, 20, 25, 30
Experiment

* Distribution

<table>
<thead>
<tr>
<th>Grid</th>
<th>Random</th>
<th>Cluster</th>
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</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Grid Image" /></td>
<td><img src="image2.png" alt="Random Image" /></td>
<td><img src="image3.png" alt="Cluster Image" /></td>
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</tbody>
</table>
Experiment

* Distribution

- Grid + Uniform
- Random + Uniform
- Cluster + Uniform
- Grid + Random
- Random + Random
- Cluster + Cluster
Findings

* The further the target is located, the better BIGnav performs
Findings

* **BIGnav** performs better in non-uniform distributions
Findings

* The further the target is located, the better BIGnav performs
Findings

* **BIGnav** gains maximum information from each user input
Findings

* Trajectory in multiscale worlds. Though being more efficient, **BIGnav** incurs a higher cognitive load.
Experiment Summary

* The farther the target is, the better BIGnav performs
* The more non-uniform the distribution is, the better BIGnav works
* Half of the participants preferred BIGnav for being efficient and interactive
* Another half favored STDnav for being comfortable and intuitive
A map application - “3 steps to go to Paris”.
Europe map featuring large cities with their population as distribution.
A map application - “Navigate to Helsinki”. Europe map featuring large cities with their population as distribution.
Future

- Reduce users’ cognitive load while ensuring efficiency
- Provide continuous interaction & finer control
- Combine BIGnav with STDnav
Future

* Other “BIG” applications

Feedback $X = x$

Prior knowledge $P(\Theta = \theta)$

Input $Y = y$
Other “BIG” applications - BIGFile

<table>
<thead>
<tr>
<th>Category</th>
<th>Date</th>
<th>Time</th>
<th>Notes</th>
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<tbody>
<tr>
<td>CV</td>
<td>Apr 5, 2017</td>
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<td>eBooks</td>
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<td>Finances</td>
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<tr>
<td>House</td>
<td>Apr 5, 2017</td>
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<td>Miscellaneous</td>
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<td>Papers</td>
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Other “BIG” applications - BIGFile

The usual hierarchy

<table>
<thead>
<tr>
<th>Directory</th>
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<tbody>
<tr>
<td>Geography</td>
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<td>Computing</td>
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<tr>
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<tr>
<td>Transport</td>
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<tr>
<td>Health</td>
<td>Apr 5, 2017</td>
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<tr>
<td>Entertainment</td>
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<tr>
<td>History</td>
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<td>Plants</td>
<td>Apr 5, 2017</td>
<td></td>
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<tr>
<td>People</td>
<td>Apr 5, 2017</td>
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<tr>
<td>House &amp; Home</td>
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<tr>
<td>Photo</td>
<td>Apr 5, 2017</td>
<td>60k</td>
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</tbody>
</table>

Estimated shortcuts
Future
Bayesian Information Gain for Guiding Multiscale Navigation

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BIGnav Computation

Update its knowledge

Using Bayes’ theorem:

\[ P(\Theta = \theta | X = x, Y = y) = \frac{P(Y = y | \Theta = \theta, X = x)P(\Theta = \theta)}{P(Y = y | X = x)} \]

where

\[ P(Y = y | X = x) = \sum_{\theta'} P(Y = y | \Theta = \theta', X = x)P(\Theta = \theta') \]
BIGnav Computation

Calculate the expected information gain

\[ IG(\Theta|X=x,Y) = H(\Theta) - H(\Theta|X=x,Y) \]

Using Bayes’ theorem:

\[ IG(\Theta|X=x,Y) = H(Y|X=x) - H(Y|\Theta,X=x) \]

where

\[ H(Y|X=x) = \sum_y P(Y=y|X=x) \log_2 P(Y=y|X=x) \]

and

\[ H(Y|\Theta,X=x) = \sum_{y,\theta} P(\Theta=\theta)P(Y=y|\Theta=\theta,X=x) \log_2 P(Y=y|\Theta=\theta,X=x) \]