The Street Score project and Visual Perceptions of Safety: Scope for Improvement?

Knowledge Lab Team Presentation

Nandana Sengupta

February 22, 2016

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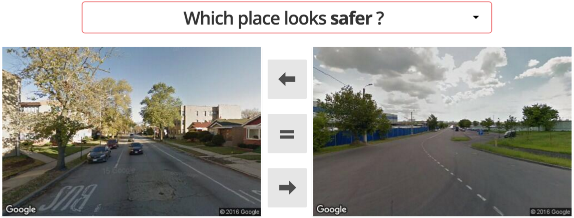
- 

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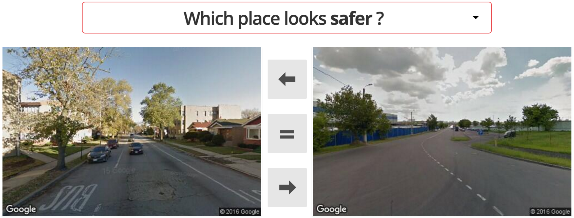
- 

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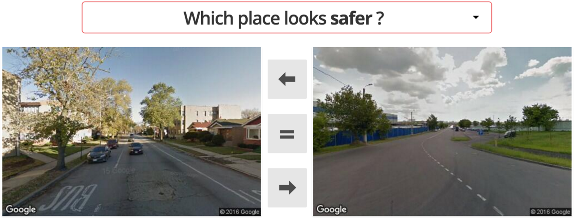
- 

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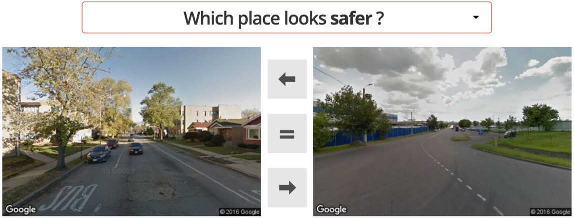
- 

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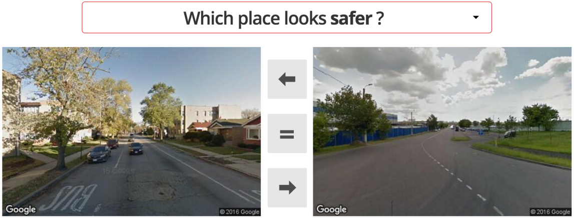
- 

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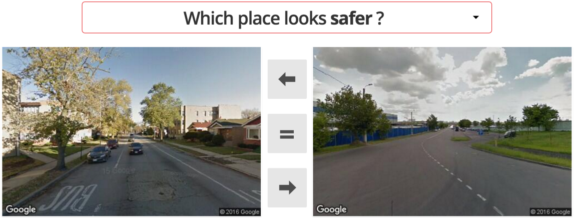
- 

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- Number of images: 4109 , Number of participants: 7872 , Number of comparisons: 208738.

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  - Use Active Learning techniques for collecting data.
    - Might require setting up a new survey

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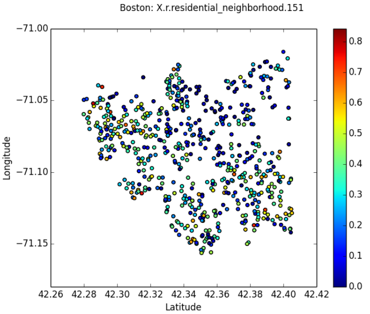
  - User Input: Latitude and Longitude

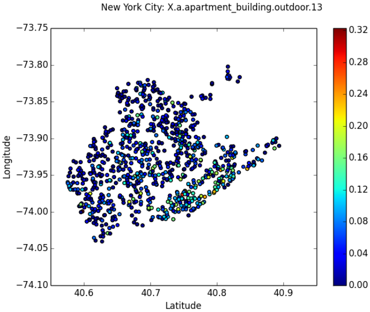
Feature Extraction using Deep Learning Software

Top 3 Predictors: (office building, apartment building, hospital)

Top 3 Predictors:(yard, residential neighborhood, driveway)

Feature Extraction: distribution across physical area





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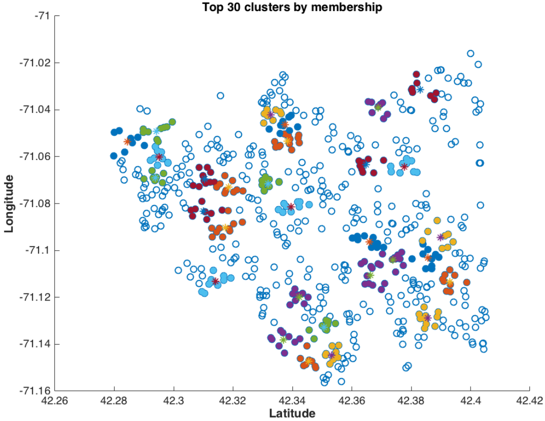
  - Features for each cluster is the weighted average of member images
- Now ready to run different ranking techniques

Clustered Data for Boston: Top 30 clusters



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- Depending on results, consider possibilities for applying active learning techniques for future data collection.

Thanks!