Estimating mode counts and distances based on phone-sensed predictions

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Introduction

Travel surveys gather information about travel behavior and often ask participants to manually provide information. To lower user burden, smartphone-based travel surveys use phone sensors to predict trip information. These sensed predictions are not perfectly accurate.

Goals:

- Provide uncertainty ranges on value estimates that capture the actual value for mode count and distance metrics

Inputs

- A set of phone-based predictions for counts or distances
  - From what we call an *evaluation dataset*
- A column-normalized confusion matrix from an existing classifier, so P(true mode | predicted mode) for each entry
  - From what we call a *computation dataset*

Method

For each mode, we use the probabilities to determine the distribution of true counts given predicted counts. Then we add up the true counts from each predicted mode to get the total true count.

For variances, we use a similar method in which we sum up the variances from each predicted mode.

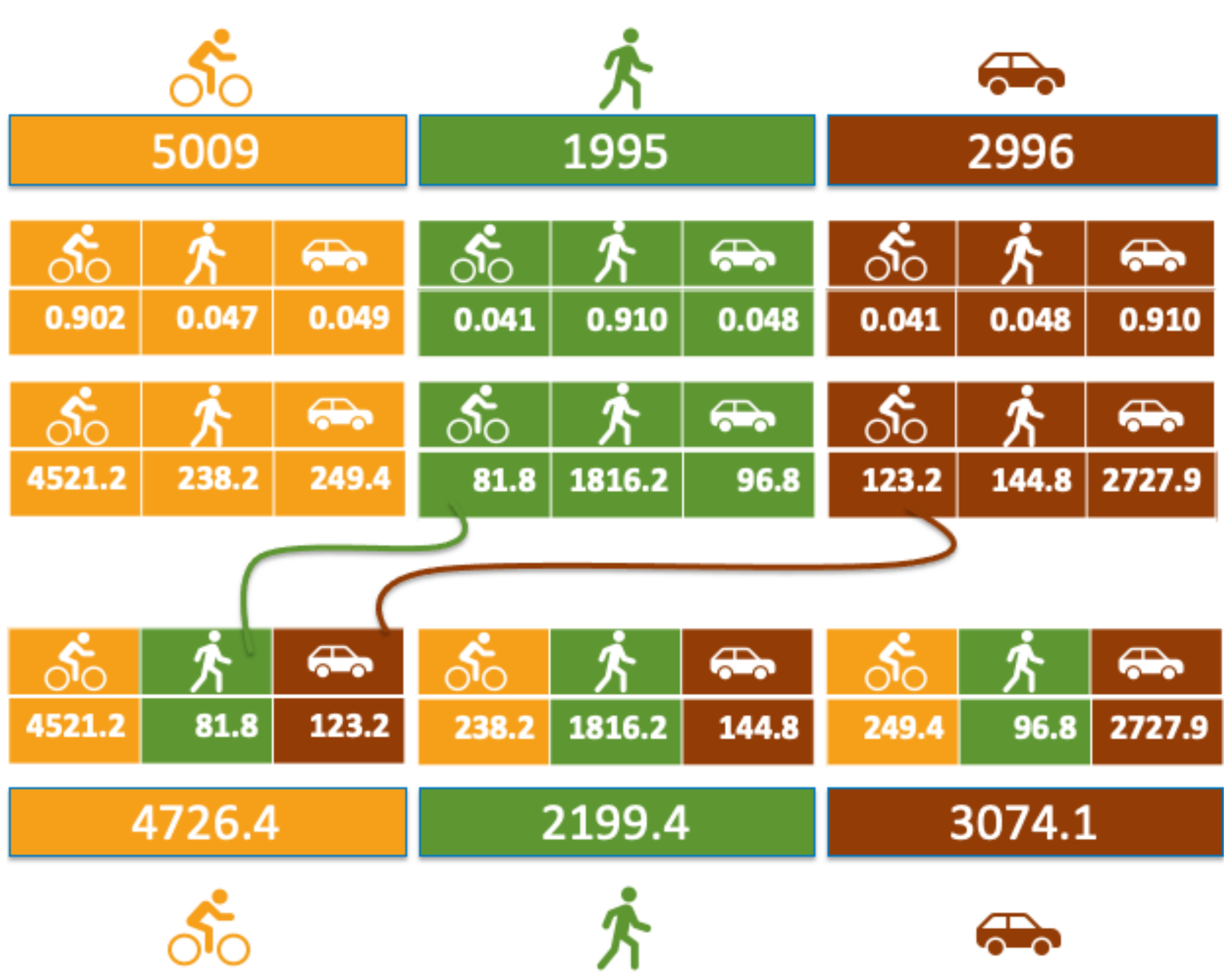


Figure 1. Worked example for mode counts, of the method for computing expected value.

Results

We evaluated our method using three different real-world datasets:

- MobilityNet: trips created by following predetermined routes
- All_CEO: trips from e-bike programs by the Colorado Energy Office
- Durham: trips from a similar program in Durham, North Carolina

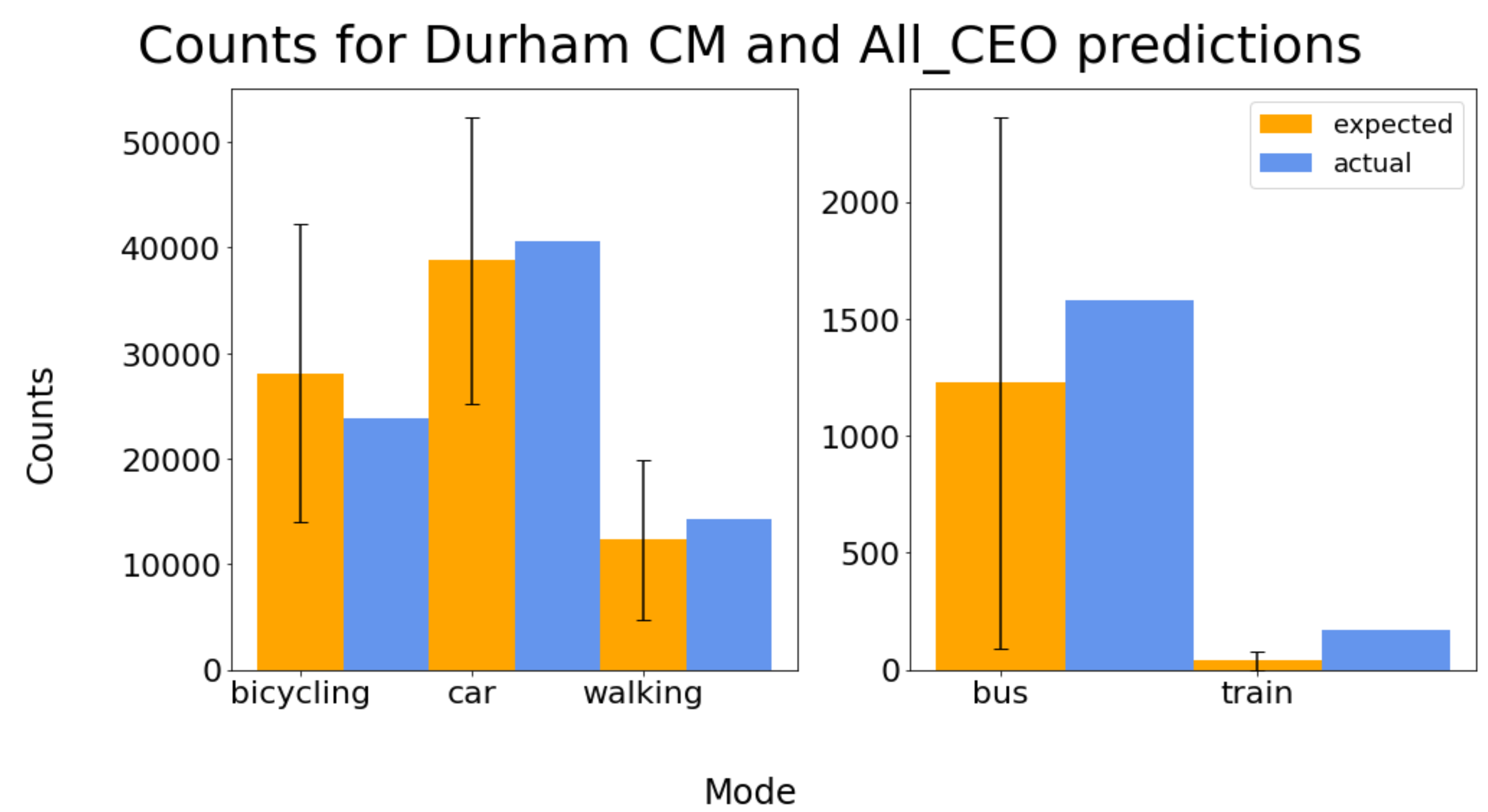


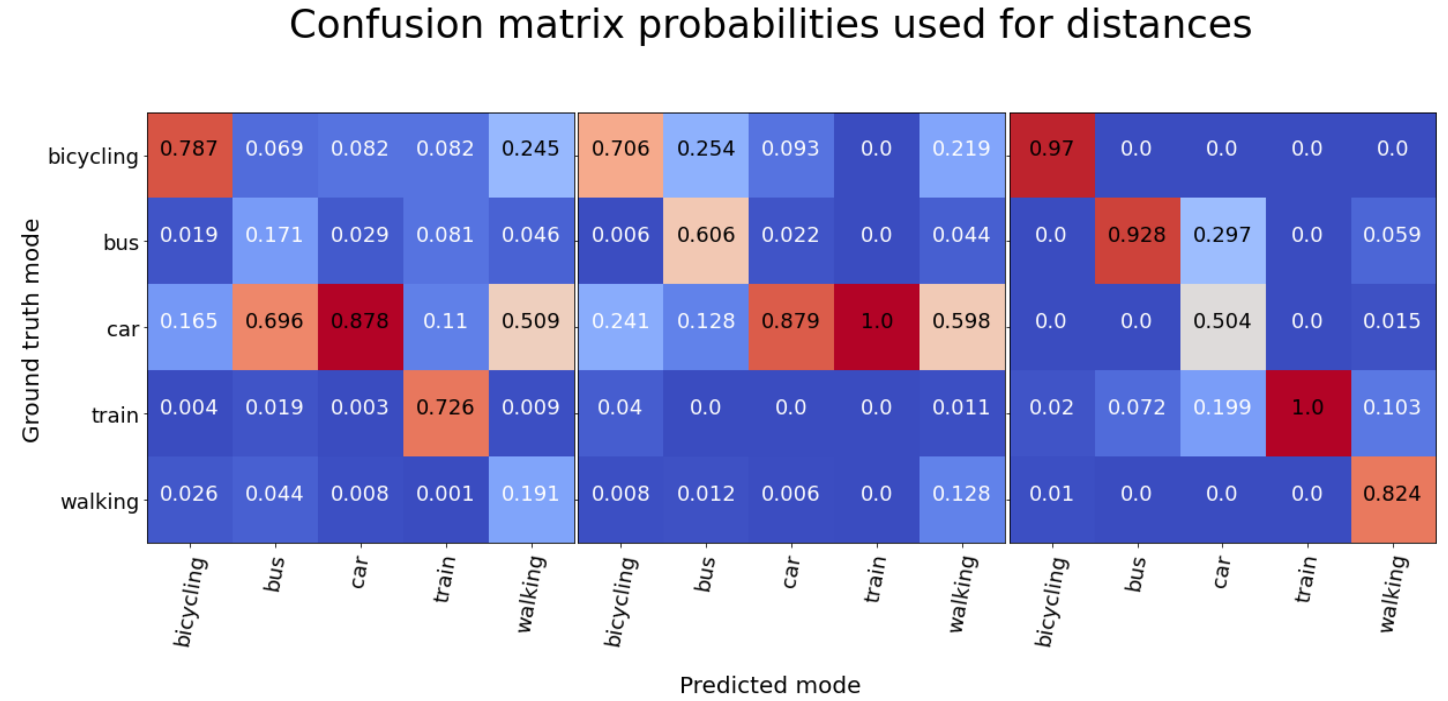
Figure 2. Results when using Durham as the computation dataset and All_CEO as the evaluation dataset for mode counts.

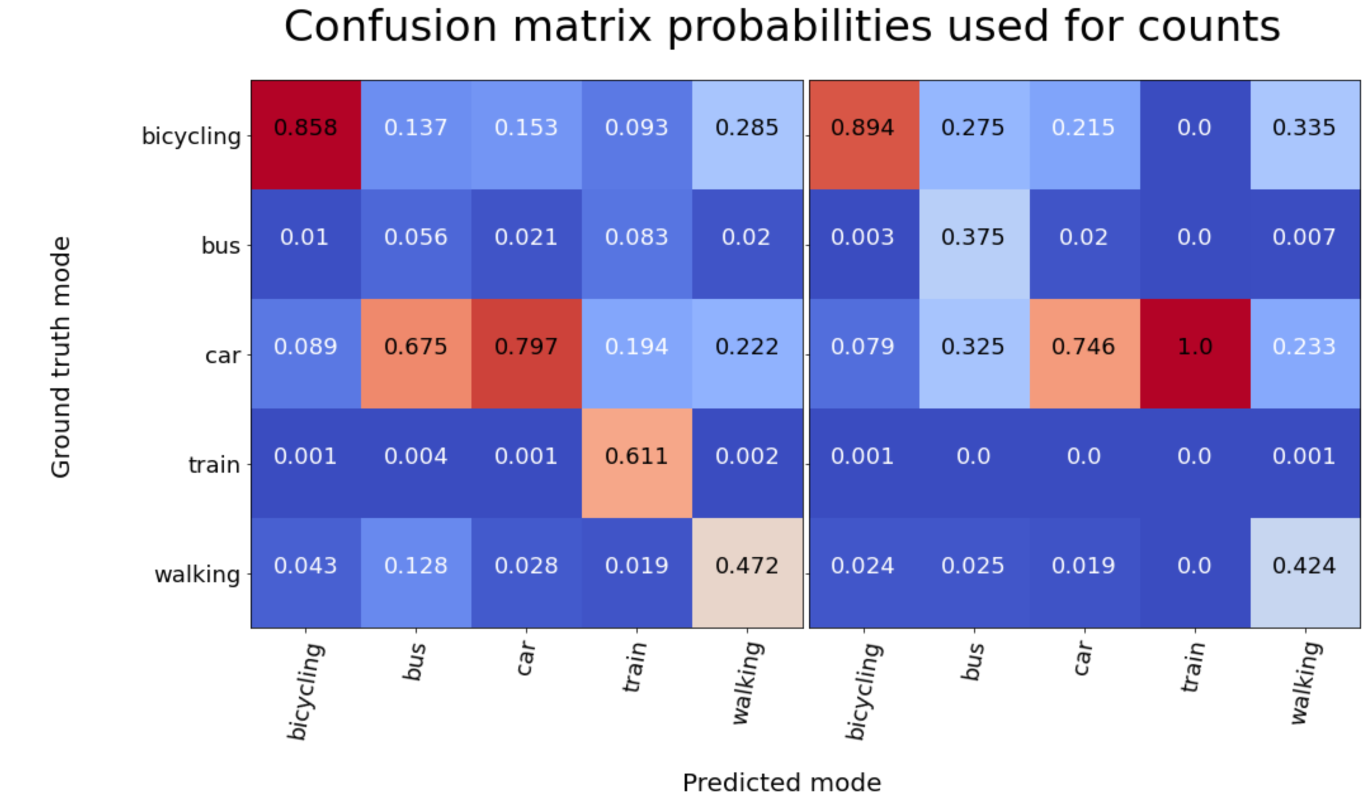
Metric	Computation dataset	Evaluation dataset	Uncertainty range captures actual value?
Distance	MobilityNet	All_CEO	✗
Distance	MobilityNet	Durham	✗
Distance	All_CEO	All_CEO	✓
Distance	All_CEO	Durham	✓
Distance	Durham	All_CEO	✓
Counts	All_CEO	All_CEO	✓
Counts	All_CEO	Durham	✓
Counts	Durham	All_CEO	✗

Figure 3. Summary of results over all datasets. In the last experiment, the uncertainty range for the mode train failed to capture the actual count for train.

Discussion

Distance probabilities for All_CEO (left) and Durham (middle) are more similar than MobilityNet (right). This explains why using MobilityNet as the computation dataset failed to produce the expected results.





Count probabilities for All_CEO (left) and Durham (right) are still different, namely for the mode train. This explains why using Durham as the computation dataset and All_CEO as the evaluation dataset failed to produce the expected results.

Conclusion

- When probability distributions of the computation and evaluation dataset are too different, uncertainty ranges fail to capture the actual values for all modes. This can be improved in future work, using prior mode distributions to adjust probabilities.
- When fully implemented, we can reduce mode labeling requirements, and mode usage can be calculated over multiple users and over a span of time.

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