

# Building a Natural Language Understanding Module

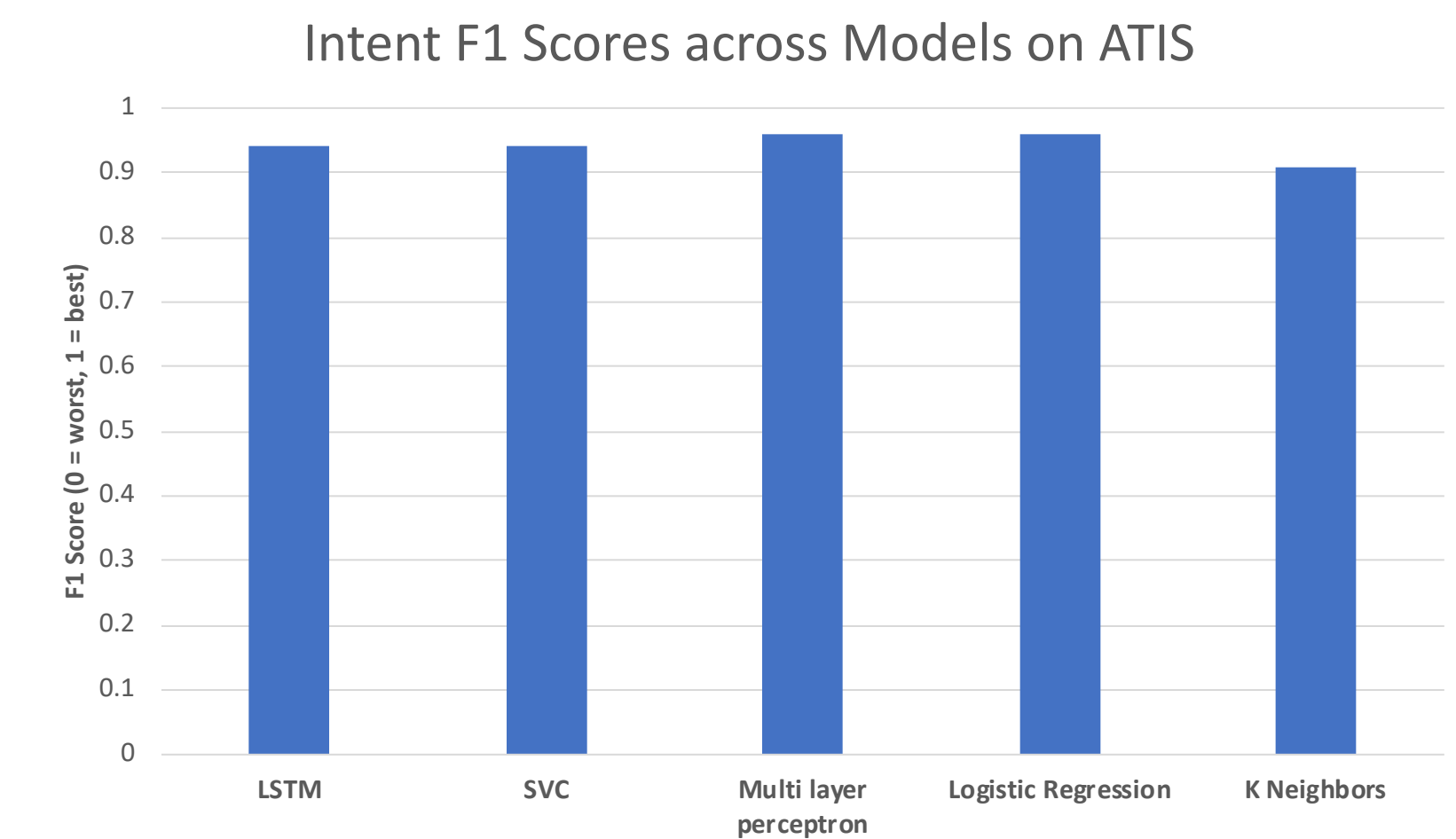
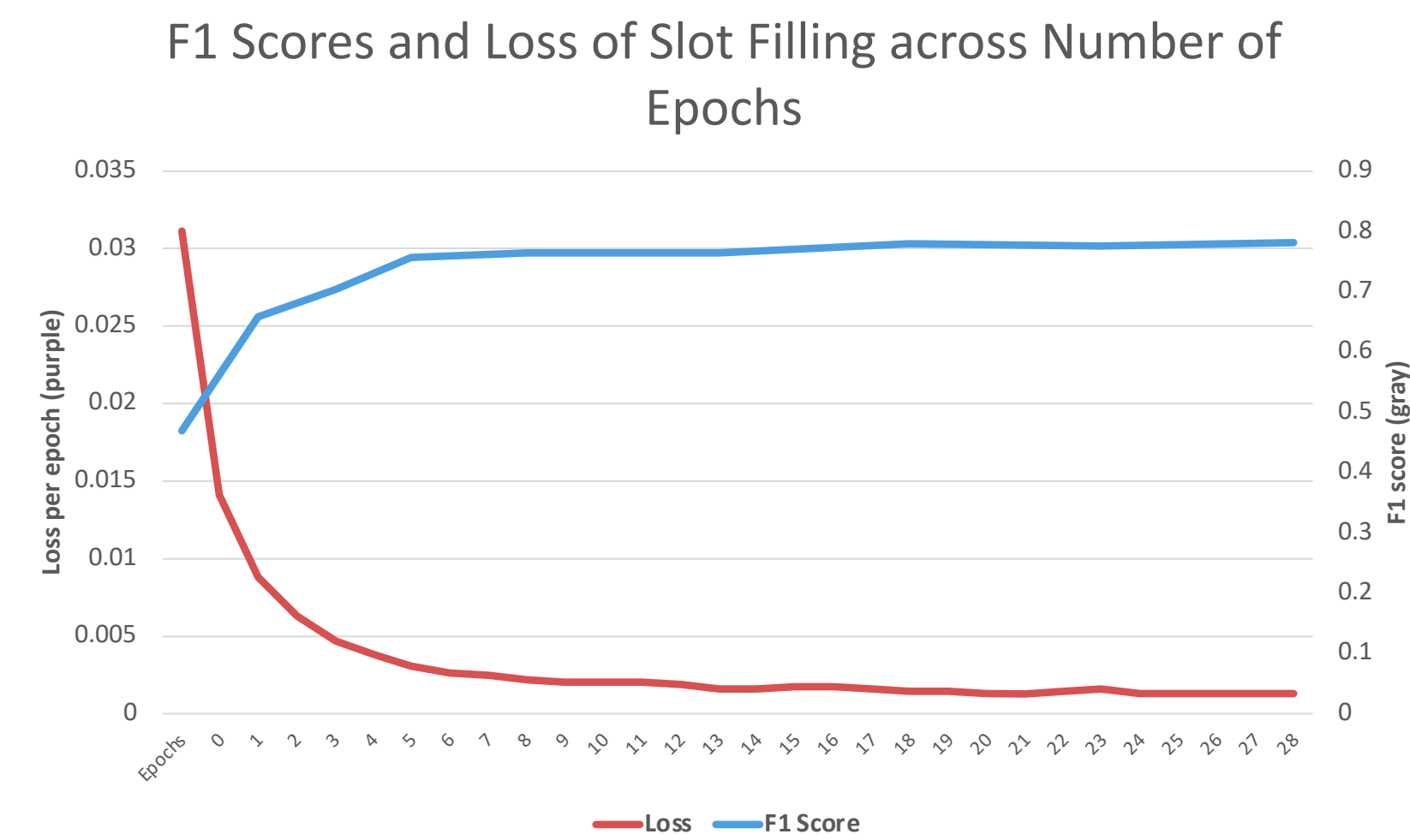
Mckenna Brown (mckennab@andrew.cmu.edu)

Advisors: Maxine Eskenazi, Shikib Mehri

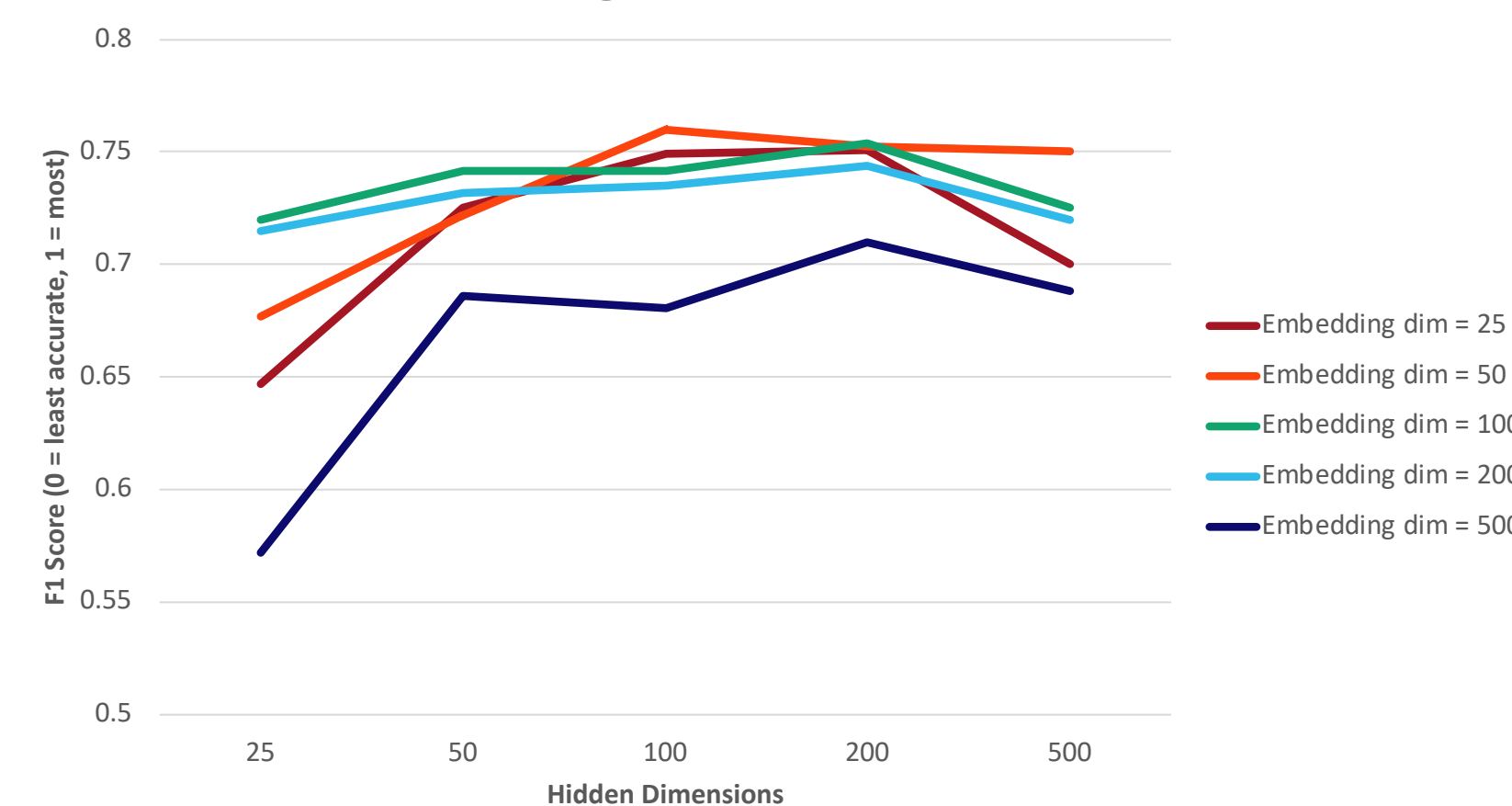
## Summary

- Creates a general and extendable **Natural Language Understanding (NLU)** module
- Task-oriented NLP use cases are in increasing demand
- Takes a transcribed sentence and predicts:
  - Intent: the general intent behind the sentence
  - Slots: the key details provided in the sentence
- Uses various methods including:
  - Support Vector Machines (SVMs)
  - Logistic Regression
  - Long Short Term Memory Networks (**LSTMs**), a type of **Recurrent Neural Network**
- Will be made open source for use in the Dialog research community

## Results/Discussion



F1 Scores of Slot Filling with LSTMs across Embedding and Hidden Dimensions

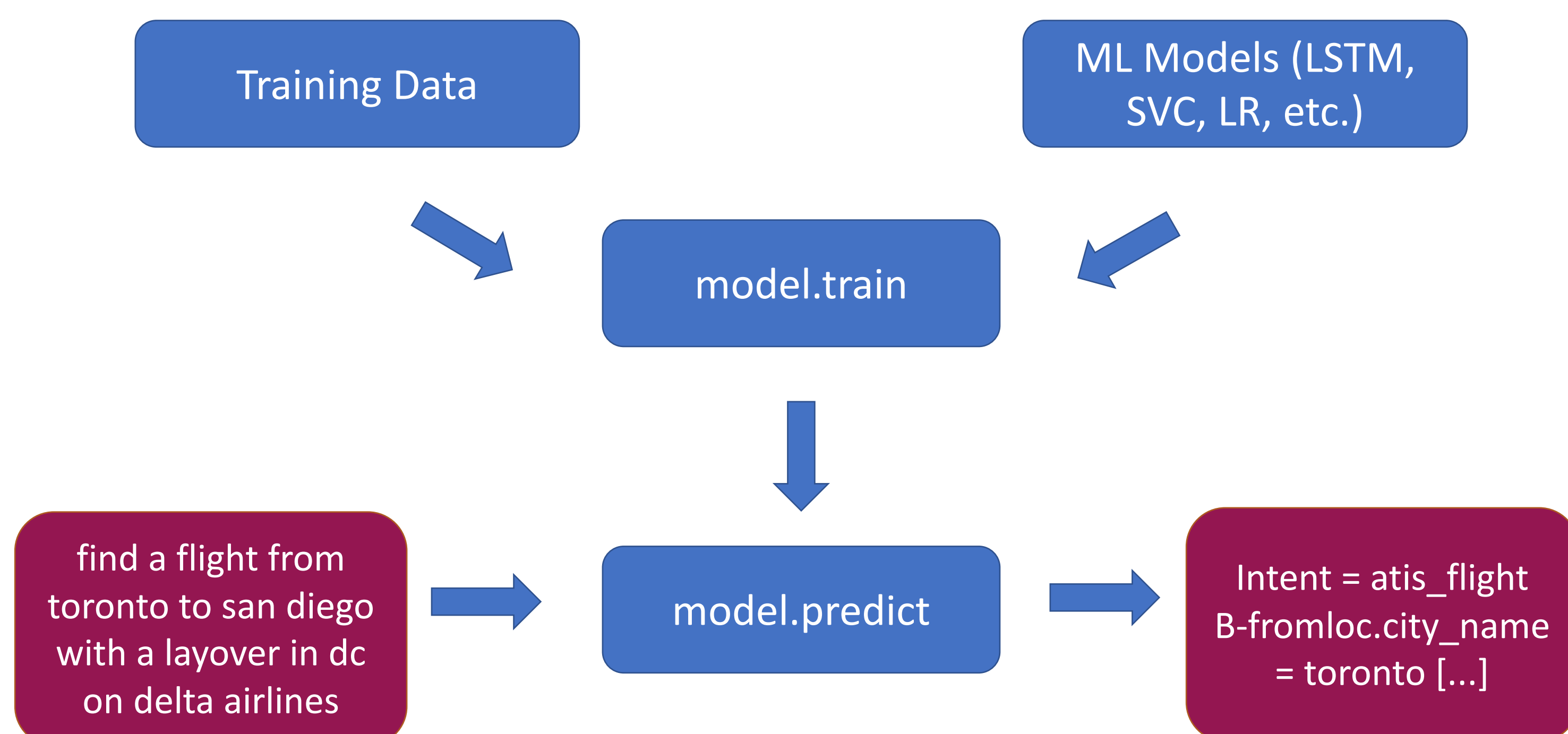


Data for both above graphs was gathered with Loss = 0.01, batch size = 10 for LSTM slot filling in ATIS. An embedding dimension of 50 and hidden dimension of 100 maximized accuracy, and 10 epochs were chosen for efficiency.

Across various ML models Intent Classification performed similarly well, with F1 scores above 0.9

- On ATIS intent classification achieved high accuracy (F1 = .94 - .96)
- In a more complex dataset (MultiWOZ), Intent F1 of .755 was achieved
- Slot Filling reached an F1 score of .760 on ATIS
- Top challenge with Slot Filling on ATIS involved correcting for skewed dataset
- Including pre-trained word embeddings from Google News lowered accuracy for both intents and slots

## Methods:



- Separate models for Intent Classification and Slot Filling
- Any ML model with a train and predict feature can be used
- Many common ML models were analyzed, including LSTMs which dynamically include past context

## Conclusions

- Handling similar but unseen words (such as “November” vs. “December”) was not assisted by decreasing vocab size or including word embeddings
- In skewed datasets, similar majority class terms were used instead of the minority versions
  - A minority class utterance might slot “Monday” as “B-depart\_date.day\_name” while it should have predicted “B-day\_name”
- Combining intent classification and slot filling into a single model could be used to help account for slot filling’s failures on minority classes
- Incorrect/Correct scoring on results can be enhanced to distinguish between slightly wrong and completely wrong predictions
  - With IOB tagging, mistakes such as “B-depart\_time.period\_of\_day” instead of “I-depart\_time.period\_of\_day” are less harmful and could be fixed with simple rules
- Extending the analysis over several datasets could enhance database-independent models