Prioritization Support Tools for Emergency Triage

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Our Models

Predictors:

- Age
- Sex
- Temperature
- Pulse
- Systolic blood pressure
- Respiration rate
- Oxygen saturation
- Mode of arrival (e.g. Ambulance)
- Chief complaints: Abdominal Pain, Chest Pain, Fever, Nausea, etc.

Critical Indicators:

- Death, **or**
- Admitted to ICU, **or**
- Admitted to operating room, **or**
- Admitted to cardiac catheterization suite

Priority Rating:
Based on the probability of the binary outcome, we can make a recommendation for ESI rating for each individual.

Text Embeddings

- Up to 5 "reason for visit" (RFV) codes provided for each patient
  - Classified into binary categories for baseline model
    - (Neurological Complaint, Cardiovascular Complaint, etc.)

- RFVs are in detailed natural language
  - "Cancer: respiratory tract, bronchus, larynx, lung, throat, trachea"
  - Distributional hypothesis: "words that have similar context will have similar meanings" (Harris, 1965)

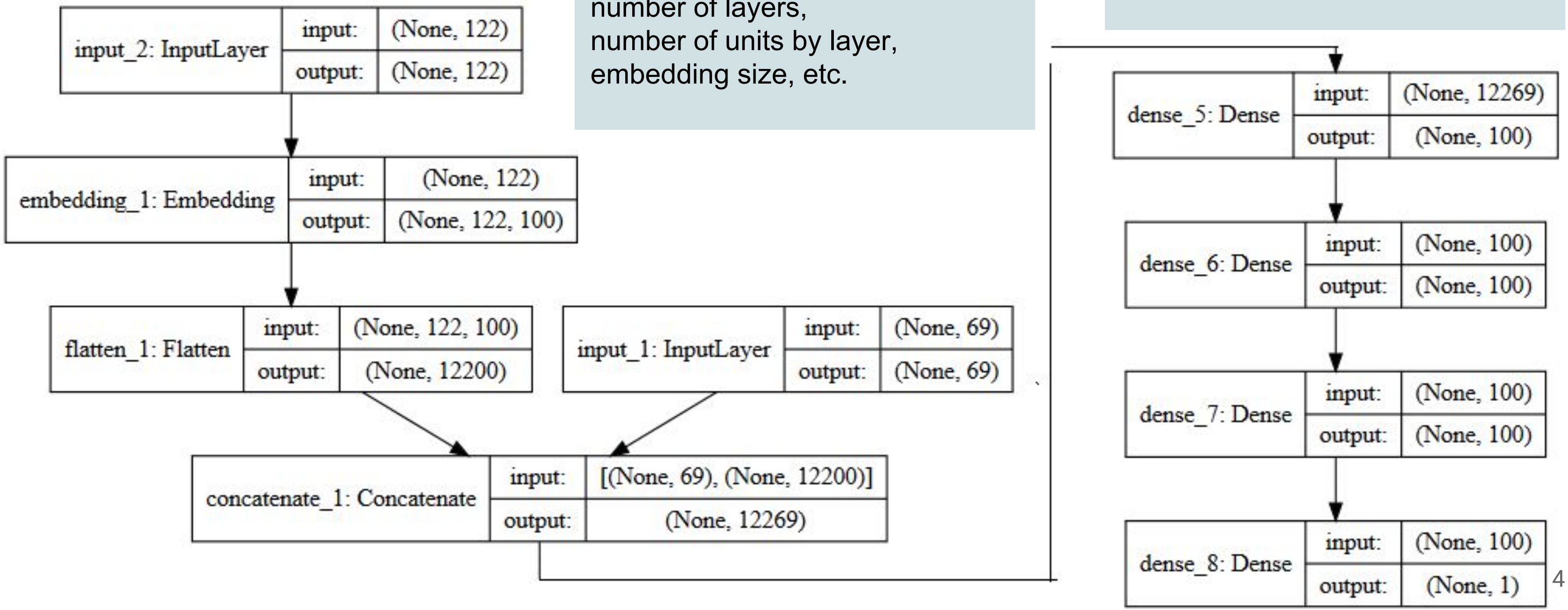
- Vocabulary size: 1603 words
  Average text length: 12.6
  Max text length: 122

NN with Embeddings Architecture

KERAS / Tensorflow
Google Cloud

Tuning Hyper-parameters:
Regularizations, learning rate,
epochs, optimizers,
number of layers,
number of units by layer,
embedding size, etc.

Activation = Relu, Sigmoid
Optimizer = nadam
Loss = 'binary_crossentropy'



Results so far

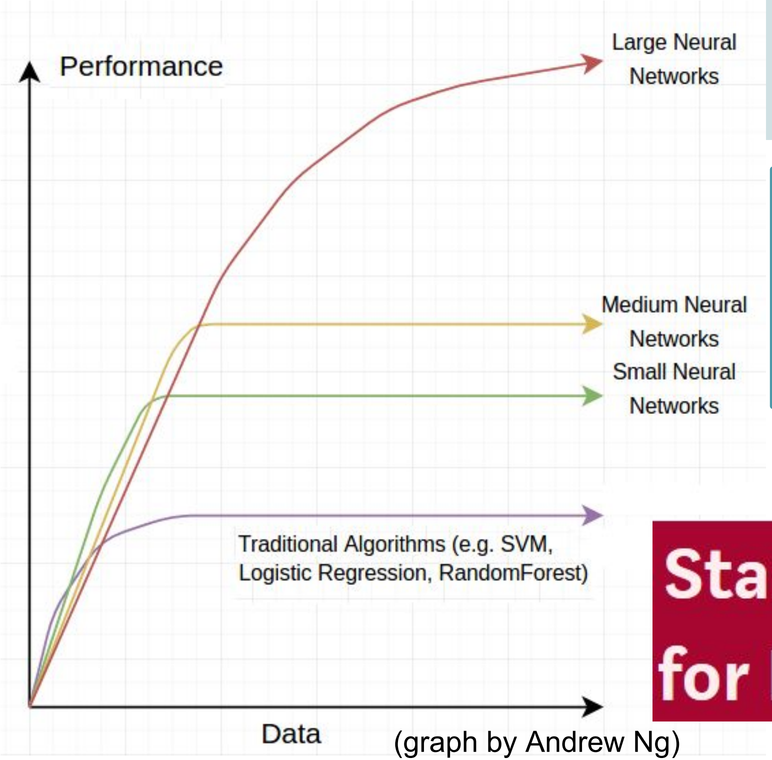
Using data for 2009 Only: 24K records (CDC has data from 1992 to 2015)

Model ID	**Model**	**AUC ROC** **10 Fold Cross Validation**
LR_BAS	Baseline LR (Logistic Regression) Matches published paper	83.36% (+/- 0.02%)
LR_RVF	LR_BAS + RVF hierarchical medical codes as vectors (to capture semantic similarity)	83.93% (+/- 0.02%)
LR_MH	LR_RVF + MSA and some Chronic Illnesses	84.55% (+/- 0.01%)
NN	Features of LR_MH into a Neural Network	85.49% (+/- 0.02%)
NN Embeddings	NN + Embedding for RVF text (one run with 100 epochs: roc = 86.22%)	

Note: AUROC for Mortality: ~ 93%

Why try NN on healthcare triage data?

- EHRs has increased dramatically
- Opportunity to refine prediction algorithms
- ER Stakeholder: LR "assumes linear separability ..., we know that we have co-morbidities that are non-linear"



(graph by Andrew Ng)

Research at Google

"Scalable and accurate deep learning for electronic health records" (Jan 2018)

Stanford AI for Healthcare

MIT CS & AI Lab (May 2017)

"Clinical Intervention Prediction and Understanding using Deep Networks"

Model-Viz Next Steps

Modeling

- Review data downloaded from 2007 to 2015 for NN models
- Test CNN model
- Run NN models with more data
- Systematic hyperparameter tuning
- More feature engineering
- Mapping prediction probabilities to ESI levels

Design Visualizations for Model Interpretation

- What the model learned
- How ESI levels move with the model
- Specific predictions’ interpretation

Service Layer

Progress

- Integrated API service daemon with preliminary model
  - Currently receiving and outputting JSON
  - Limited error catching for requests
- Created rudimentary client
  - Passess JSON request over http
  - Parses response and prints as text
- Begun API security additions
  - Exploring the use of token security

Issues still outstanding

- Determine which authentication method to use
- Convert JSON I/O to FHIR
- Use end-to-end Encryption

Service Layer Next Steps

Security Improvements

- Implement Authentication
  - OAuth
  - Password
- Implement SSL

Client/API Improvements

- Implement FHIR on API and Client
- Rebuild client in Javascript
- Begin building delivery vehicle