Unstructured Clinical Notes Mining for Mortality Prediction

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Problem Statement & Motivation

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Deidentified information   Patient Problems (as assessed)   Patient Measurements
Patient Condition (as observed)

Figure: Sample Color Annotated Clinical Note

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Task

We want to do 1 week, 1 month, 6 month & 1 year long mortality prediction

Dataset[1]

MIMIC–III v1.4 dataset

- Publicly available de-identified health-related data associated with over 40,000 patient
- Recorded in critical care units of the Beth Israel Deaconess Medical Center between 2001 and 2012.
- Dataset contains information on patient demographics, vital sign measurements, lab test results, clinical procedures, medications, caregiver notes, imaging reports, and mortality labels.

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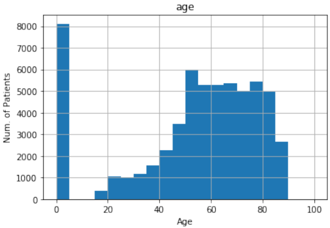
Dataset is in form of multiple tables. For our purpose we only selected

- Admissions Table – ICU Stay and other info
- Patients Table – Patient level and demographic information
- Notes Table – clinical free form textual description

Patient Cohort Selection



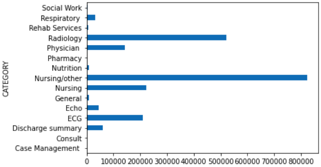


Figure: Age and Frequency Distribution of Type of Notes

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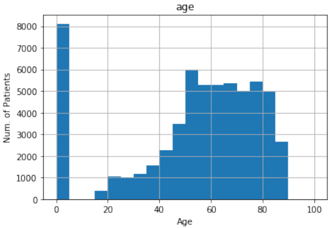

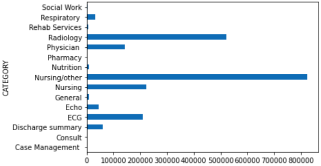

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Inclusion Exclusion Criteria

We retrieved set of

- Adult patients ($\geq$ 18 years) with at least one associated note from the database.
- We extracted `Nursing Progress Note` from the dataset.

Dataset Preprocessing

- We used **Big query** and its SQL dialect for our cohort selection.
- Mean number of notes per hospital admission is 32 (Median: 15)
- We concatenated all notes of a particular patient with the same hospital admission id.

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Survival Label

- 'surv_day', which is essentially the number of days the patient has survived after discharge from the hospital

Attribute Label	Frequency (Prevalence)
one_week_mortality	258
thirty_day_mortality	736
one_eighty_mortality	253
one_year_mortality	653

Table: Prevalence in Survival Class

Workflow

- Patients were randomly split into train (70%), validation (15%), and test (15%) sets.
- Since we have a limited number of True labels for any class, (thirty_day_mortality has train prevalence as 11%). It has a class imbalance, to deal we this we did a minority class oversampling.
- To keep things simple and interpretable, we tokenized our notes and then used the `CountVectorizer` on it.

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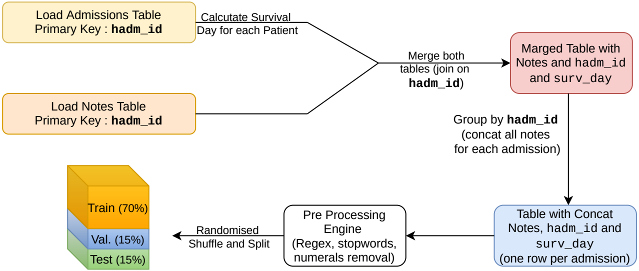

Figure: Workflow of data preparation

Model Description

- We used bag of words approach with logistic regression for initial model building → we can plot the most important features for each **True** and **False** survival class.
- **True** = [`ml, should, time, it, been, cm, cc, dr`]
- **False** = [`po, off, c, i, level, to, s, at`]
- Added new stop words list → removed them from our vocabulary

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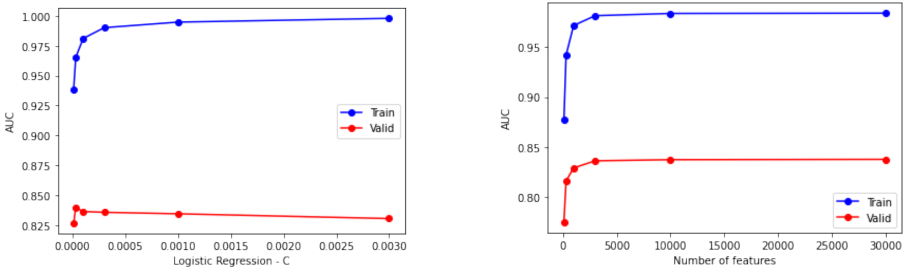


(a) C Value

(b) Number of Features

Figure: Choice of Hyperparamter for logistic regression

Evaulation Metrics

- We have used Area under the receiver operator curve (**AUC**) to judge the performance of the model. This metric is consistent with other studies published in the domain.
- Apart from AUC, we reported **Accuracy** as well. Accuracy is defined as $\frac{\sum \mathrm{TP} + \sum \mathrm{TN}}{\sum \text{Total Population}}$.
- We also reported **Specificity**, which is defined as

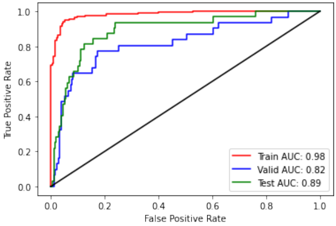
$$\frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false positives}}$$

Results

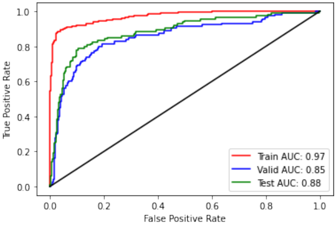
Model →	Logistic Regression			Decision Tree		
Metric →	AUC	Accuracy	Specificity	AUC	Accuracy	Specificity
7 day Mortality	0.891	0.766	0.762	0.743	0.765	0.767
30 day Mortality	0.884	0.855	0.862	0.809	0.810	0.811
6 month Mortality	0.641	0.599	0.597	0.554	0.662	0.671
1 year Mortality	**0.607**	0.569	0.567	0.550	0.542	0.540
Model →	XG Boost			SVM		
Metric →	AUC	Accuracy	Specificity	AUC	Accuracy	Specificity
7 day Mortality	**0.899**	0.834	0.834	0.739	0.679	0.68
30 day Mortality	**0.926**	0.906	0.915	0.665	0.705	0.744
6 month Mortality	**0.678**	0.640	0.640	0.569	0.600	0.609
1 year Mortality	0.604	0.597	0.602	0.500	0.515	0.536

Table: Evaluation Metric for Various Models

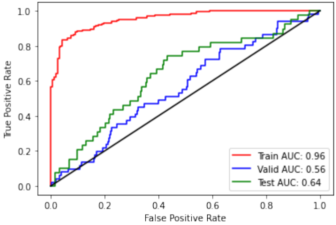
AUC Curve



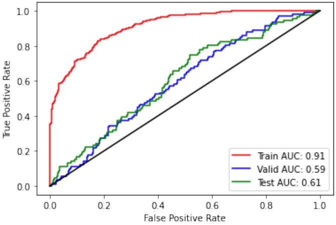
(a) 7 day mortality



(b) 30 day mortality



(c) 180 day mortality



(d) 365 day mortality

Key Inferences

- Comparison with Other State of Art Mortality Predictors from Nursing Notes

Author $\rightarrow$	Rajkomar et.al	Craig et.al	Our Approach
AUC	.94	.70	0.89
Approach	DL & Fusion	CNN	BOW

- Among all the models experimented Logistic Regression and XG Boost performed better compared to others.
- The best AUC was achieved for 30 day mortality prediction and performance drops as we aim for 6 month or 1 year long mortality prediction.

Surival Analysis using Sentiment of Clinical Notes

- No labels $\rightarrow$ Unsupervised syntactic Sentiment Mining

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- We used Textblob NLP Library. Using `v0.16.0` we extracted two syntactic features from the notes – polarity and subjectivity
- Textblob algorithm tokenizes the text, performs POS tagging, and uses a lexicon to give a sentiment polarity and subjectivity score.

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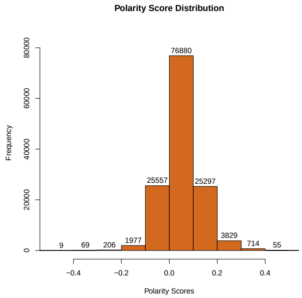

Figure: Polarity Distribution among notes

Survival Analysis

We used polarity, subjectivity with SAPSII[2] score to do the survival analysis of the patients. We partitioned the polarity and subjectivity into 4 quartiles and plotted the Kaplan Meier curve.

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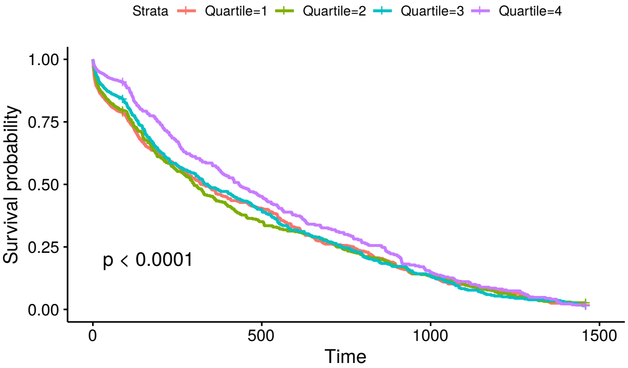

Figure: Survival Curves using Only Subjectivity and SAPSII Score

KM Curve

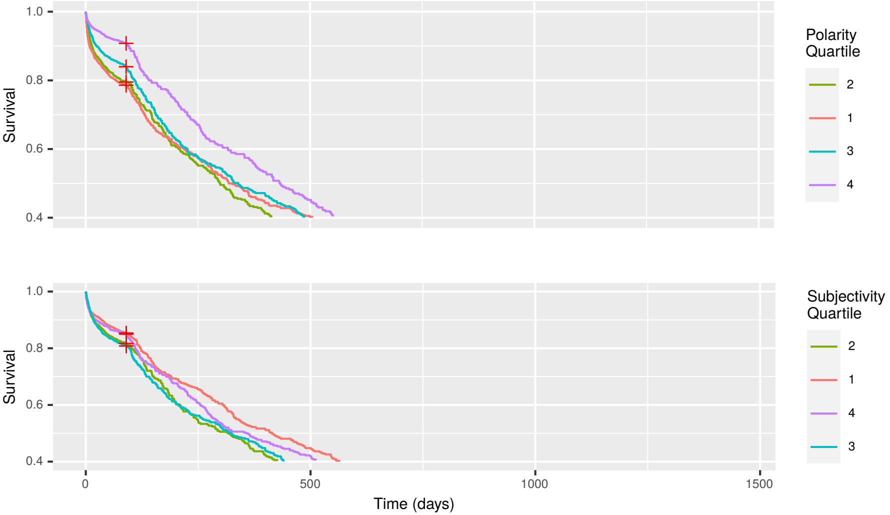

Figure: Kaplan Meier Curve

Concluding Remarks

- Unstructured text in the EHR notes contains meaningful information that can be mined for building intelligent medical decision support systems.
- If we could use the data from multiple sources, we can genuinely validate our claim.

Future Directions

- Incorporate other **structural data** (which is mostly time series such as patient measurements, etc.), **sentiments** in our model; and build a simple multimodal fusion model that can leverage both structural as well as unstructured free form text

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- Prediction of mortality remains a complex problem, however by incorporating more information extracted from unstructured data, like nursing notes it might improve the overall performance.
- Code is available in github
  `https://github.com/vntkumar8/clinical-notes-mining`

References

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Thankyou!