Prioritization Support Tools for Emergency Triage

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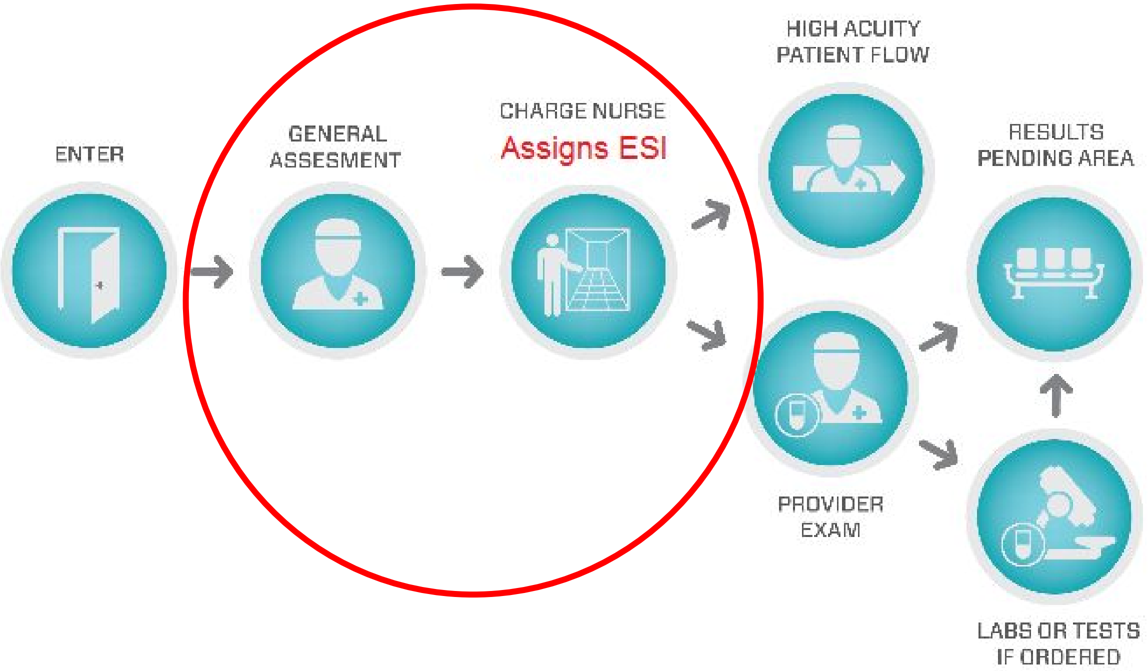
Current State



The Emergency Severity Index (ESI) is a five-level emergency department triage heuristic

Most Urgent 1 = Immediate intervention
2 = High-risk
3 = Multiple resources
4 = Single resource
Least Urgent 5= No resources

Triage nurse uses gross patient state to make a determination

Patient is then routed to appropriate care based on ESI rating

ESI rating is correlated to the wait time the patient experiences

Graph baded on: http://array-architects.com/flow-improvement-opportunities-for-an-inefficient-ed/

Problems with current approach

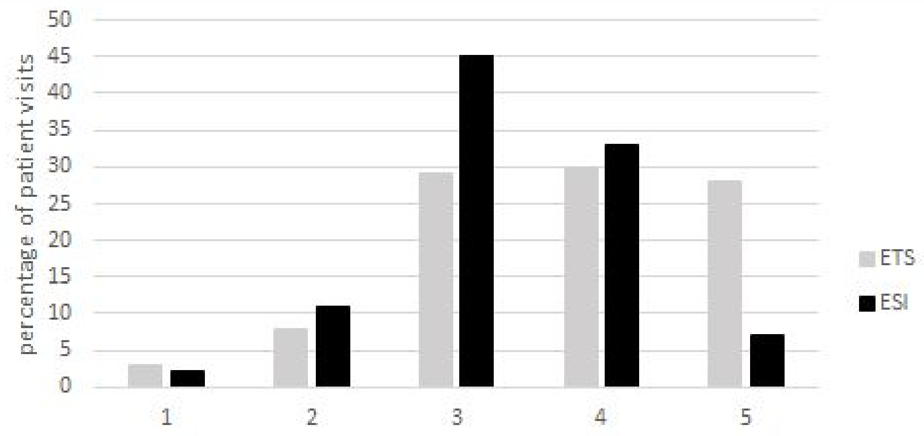


Figure 1. Severity level classification: proportion of patients assigned to each severity level for both electronic triage system (ETS) and Emergency Severity Index (ESI).

Dugas et al., "An Electronic Emergency Triage System to Improve Patient Distribution by Critical Outcomes", The Journal of Emergency Medicine. Vol. 50, No. 6. Pp.910-918, 2016.

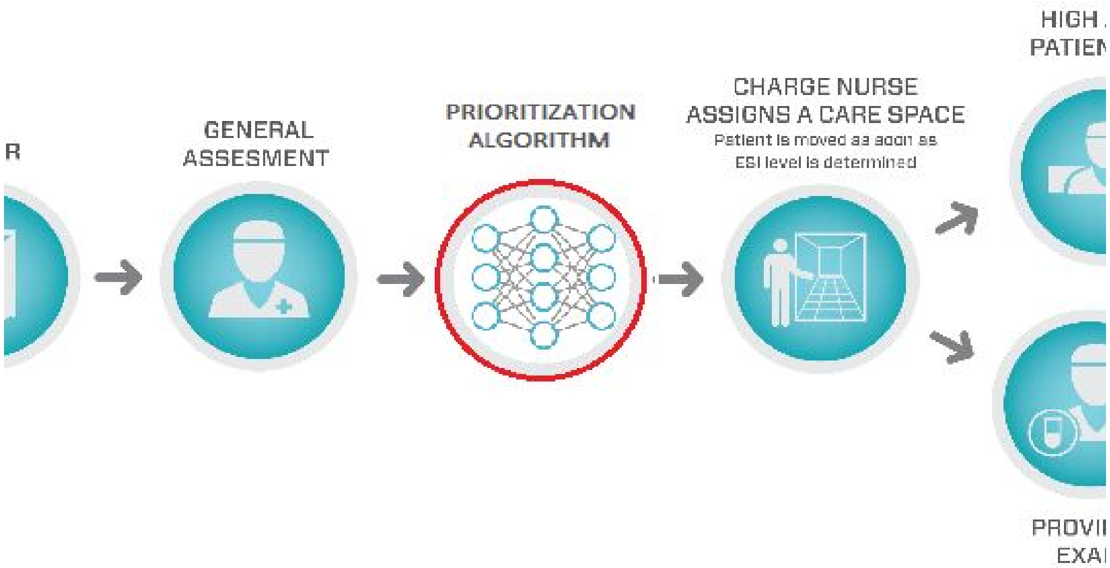
In one study, misclassification occurred in 37.8% of ESI-2 ratings, with 99.2% of these being undertriaged. 1

Subjective ESI placement results in overutilization of middle rating. 2

Critically ill patients vulnerable to worse health outcomes because of misclassification.

ETS, a logistic regression model, shows how much room for improvement there is versus ESI.

Proposed approach



Introduce a prioritization algorithm that makes use of the general assessment and previous outcome data to provide a more effective rating

Triage nurse would receive this assessment in real-time and the rationale behind it through EMR system

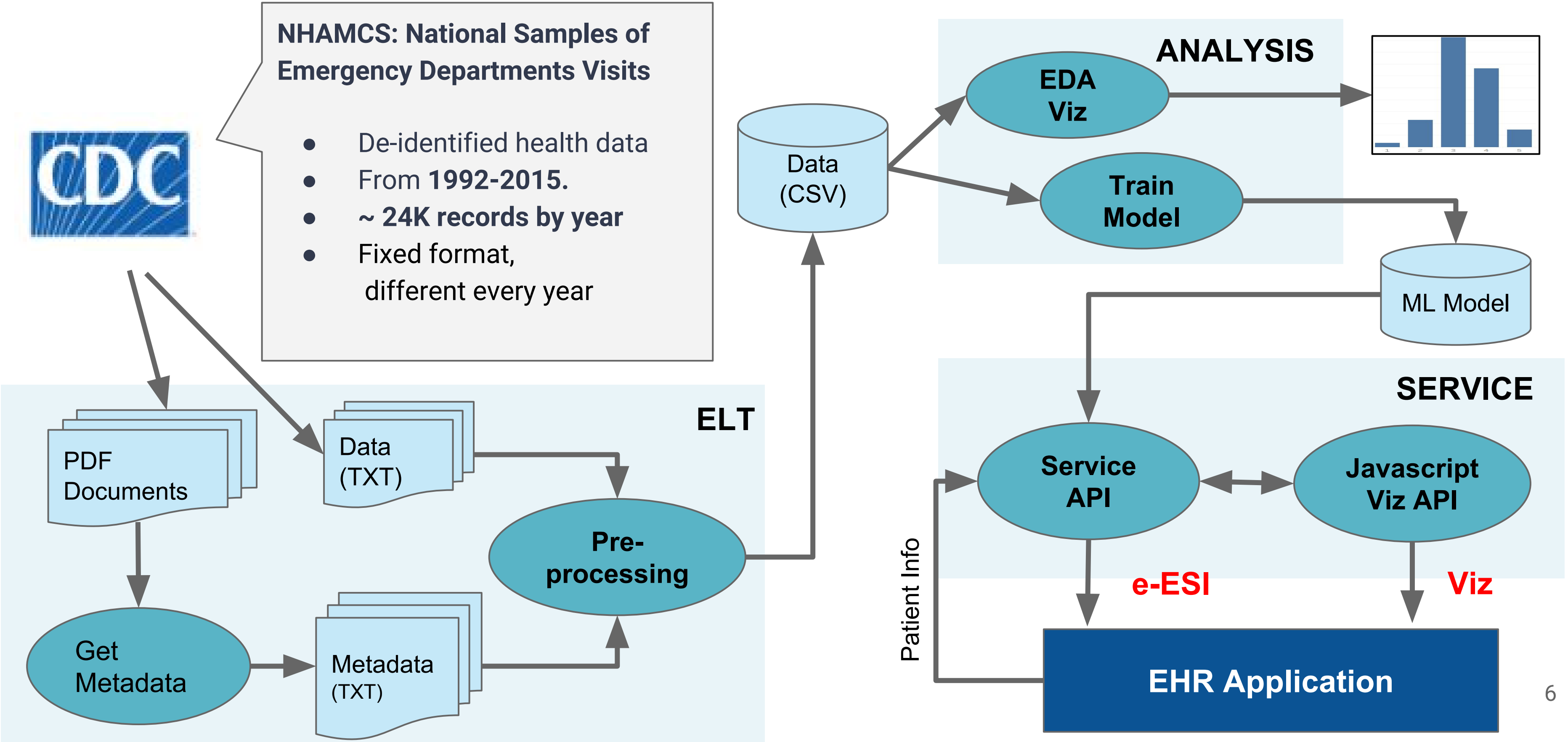
Nurse would then assign a rating to the patient

Process would continue as usual

Design Goals

- Seamless integration into current workflow
- Provide suggestions without interfering with the duties of the staff
- Empower triage staff to make more informed decisions
- Improved categorization outcomes compared to ESI and ETS

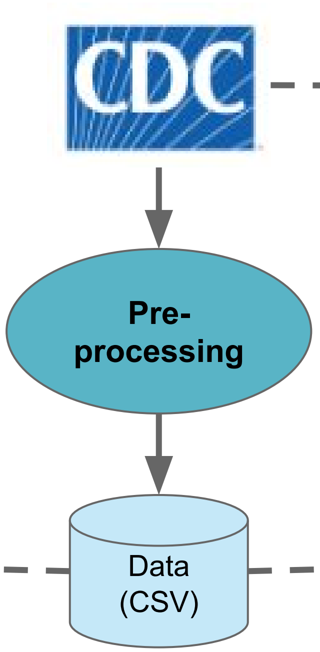
Data Sources and Pipeline



Data and Quality

Fields of interest from CDC file:

- Information collected during triage:
  - Basic demographics
  - Vital signs
  - Chief complaints
  - Mode of arrival
- ESI assigned
- Real Outcomes (e.g: Mortality, Intensive Care Unit, etc)



CDC validated data and sent representatives to hospitals to retrieve missing data

Exclusion Criteria:

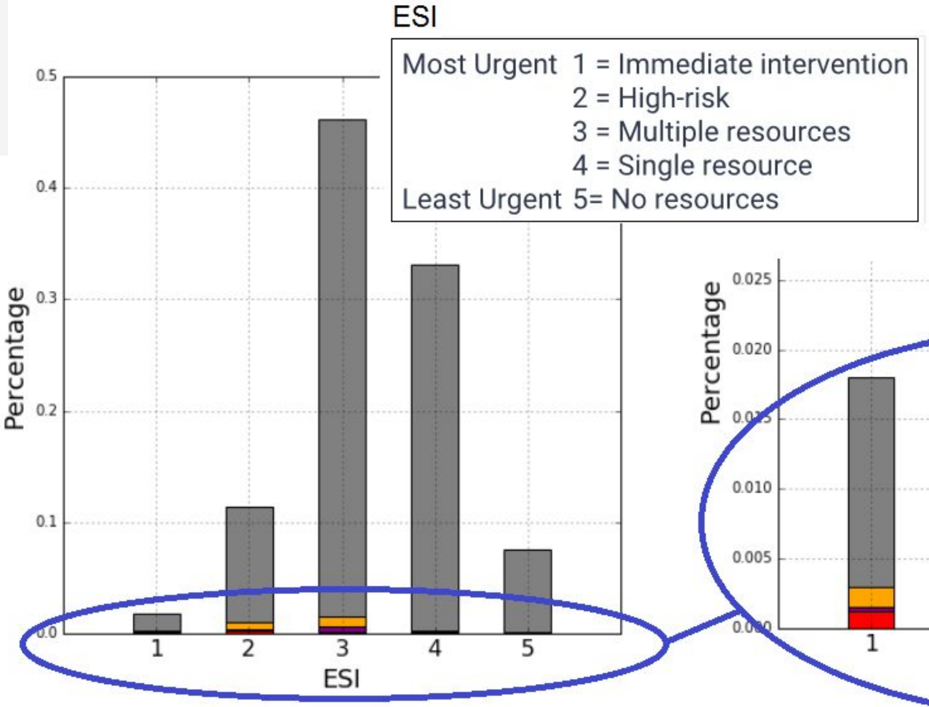
- Age < 18 or missing DOB
- Unknown outcome
- Unknown ESI
- Other

Preliminary EDA - CDC 2009 File

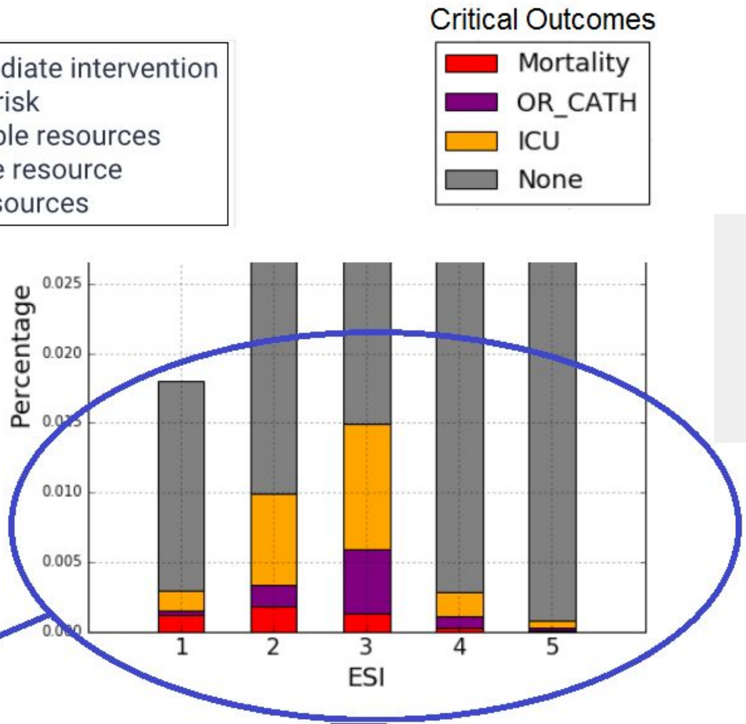
Exclusion Criteria

From: 34,942
To: 24,321

Emergency Severity Index (ESI) Distribution



Real Critical Outcomes by ESI



ESI AUC 64 %

(50% is random)

Techniques and Algorithms

- Baseline: Logistic Regression
  - Verification of data
  - Useful predictors
  - Evaluation methods
- Random Forest
  - Additional composite outcomes
- Neural Network
  - LSTM and TANN

- Optimize for
  - AUC
  - Correct classification of critical outcomes

Baseline: Logistic Regression

- The AUC is close to the result from Degas et al.
- We were able to mostly replicate their predictors and methods
- Baseline has poor accuracy for critical outcome predictions

Tune-ups:
- Optimizing C
- Choosing a regularization method
- Getting closer to Degas et al.'s AUC value

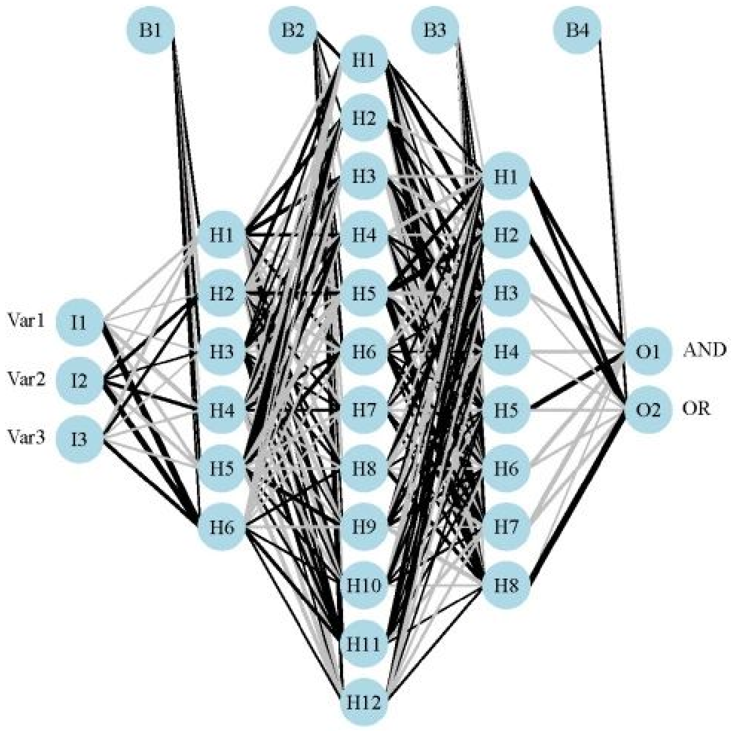
Degas et al.:
- AUC = 0.83

Logistic Regression Baseline:
- C=0.05
- L2 regularization
- Balanced regression
- AUC = 0.85

		Actual	
		0	1
Predicted	0	1805	554
	1	16	58

Challenges and Considerations

- Defining predictors
  - Some definitions from Degas et al. are unclear
  - Utilizing more information from the dataset
- Multiple Imputation
  - Degas et al. use MICE to impute missing values
  - Independently verify that there are no patterns in missing values
- Model evaluation
  - We can use the AUC, F1 score, etc., but how else can we define success when the outcome is so important?
- Distribution of ESI values
  - “Natural” versus “recommended” distributions
- Visualizing outcomes for nurses/doctors
  - Especially difficult for neural networks



Existing Research Samples

- Dugas et al., “An Electronic Emergency Triage System to Improve Patient Distribution by Critical Outcomes”, 2016.
- Levin et al., “Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared with the Emergency Severity Index”, 2017.
- Rajkomar et al., “Scalable and Accurate Deep Learning for Electronic Health Records”, 2018.