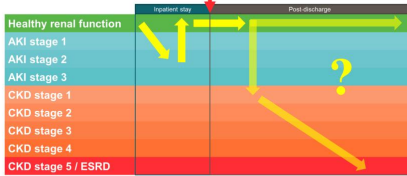


Background

- Pediatric patients with abnormal renal function during hospitalization are at risk of developing chronic kidney disease (CKD) months later.
- LPCH nephrologists do not have capacity to provide follow-up renal monitoring and care to all at-risk patients, and it is unknown which are at greatest risk.

Objective

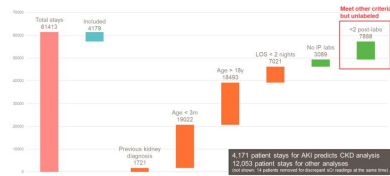
Using data available at time of discharge, can we predict the development of CKD 3-12 months later?



Data

- Data on 4,179 patients were pulled and processed

Demo	Stays	Labes (Serum Creatinine)
<ul style="list-style-type: none"> • Encrypted MRN • Sex • Ethnicity • Race • Birth date* • Death date* • Age at death 	<ul style="list-style-type: none"> • Encrypted MRN • Encrypted CSN • Admit date/time* • Discharge date/time* • DRG • Discharge disposition 	<ul style="list-style-type: none"> • Encrypted MRN • Lab name • Lab date/time* • Lab result value
Height/Weight	Diagnoses to exclude	AKI diagnosis
<ul style="list-style-type: none"> • Encrypted MRN • Height • Weight • Date* 	<ul style="list-style-type: none"> • Encrypted MRN • Encrypted CSN • Admit date* • ICD-9 or 10 	<ul style="list-style-type: none"> • Encrypted MRN • Encrypted CSN • Admit date* • ICD-9 or 10



Methods

Data processing:

- Labeled patients as CKD+/- based on lab values from 3-12 months post-discharge
- For initial models, used only serum creatinine lab values (models with additional features planned for future work)

Stratified Train/Dev/Test Split

- Classified based on outcome and number of lab values available for stratified sampling:

Outcome_Label	Count_SCr_inmeasurements	Class	Count_examples
CKD-	1-2	A-	1056
CKD+	1-2	A+	67
CKD-	3	B-	586
CKD+	3	B+	41
CKD-	4	C-	455
CKD+	4	C+	33
CKD-	>4	D-	1727
CKD+	>4	D+	206

- Train: 3128, Dev: 834, Test: 209 examples

Model Development

Developed 3 models:

- Used subset of data with **>2 SCr labs** to predict outcome using the **last 3 labs** from the stay
- Used subset of data with **>3 SCr labs** to predict outcome using the **last 3 labs**
- Used subset of data with **>3 SCr labs** to predict outcome using the **last 4 labs**

Model Specifications common to all models

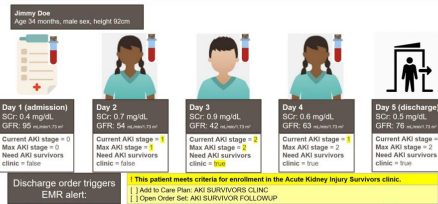
- Fully-connected models with 100 hidden layers
- Cross-entropy loss as cost function
- Adam optimization, learning rate of .0001
- Area under the ROC curve (AUC) used as model performance metric

Results

Model_Description	Dataset	Train_AUC	Dev_AUC
3 inputs, 1 hidden layer, 100 units	>2 SCr	0.7876	0.7866
3 inputs, 1 hidden layer, 100 units	>3 SCr	0.7890	0.7779
4 inputs, 1 hidden layer, 100 units	>3 SCr	0.7911	0.7762

- Inpatient lab values are predictive of developing chronic kidney disease after hospitalization
- Using the last 3 labs, I achieved a Dev AUC of 0.7866, which is clinically useful.
- Adding a fourth lab value increased the training AUC but did not improve the dev AUC, suggesting overfitting. Regularization may improve performance with four lab values.

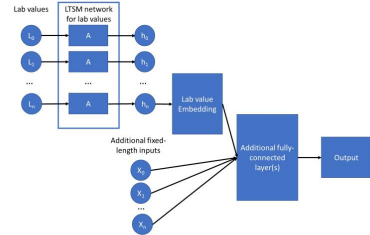
Planned Implementation



Future Work

I plan to develop more complex models and compare performance to my baseline models. Specifically:

- **LSTM** recurrent neural network that can handle variable length lab value vectors
- **Hybrid** model that uses an encoding from an LSTM recurrent neural network together with fixed-length inputs (age, height, weight, etc.) as features for fully connected model



Architecture of hybrid model planned for future work.

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