



Predicting ER Readmissions for patients with diabetes

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Project at a glance



More than 30 Million americans have diabetes



ER Readmissions within 30 days of discharge cost \$41B in 2017(comparable to \$68B for the US Education budget)

Hospitals with high readmission rates pay penalties to Medicare & Medicaid programs

10% of diabetes patients are readmitted to the ER within 30 days for an equivalent cost of \$452M annually.

My goal is to determine what are the strongest predictors of hospital readmission in diabetes patients and how well we can predict hospital readmissions using machine learning models to help hospital save million of dollars and improve quality of care.

Dataset



- Data from [UCI](#) Irvine Machine Learning Repository.
- Dataset represents 10 years of clinical care at 130 US hospitals between 1999-2008. It includes 50 features representing patient characteristics, conditions, tests and medications

Methodology



Pre processing

- Data Cleaning
- Feature Encoding
- Interaction Terms

Feature engineering

- Feature creation to understand medication dosage change
- Messy features, for ex: discharge_disposition_id had 34 categories.
- Balanced data by SMOTE
- Regularization

Modelling

Dataset shape: (97874, 57)

- Logistic Regression
- Random Forest

Models



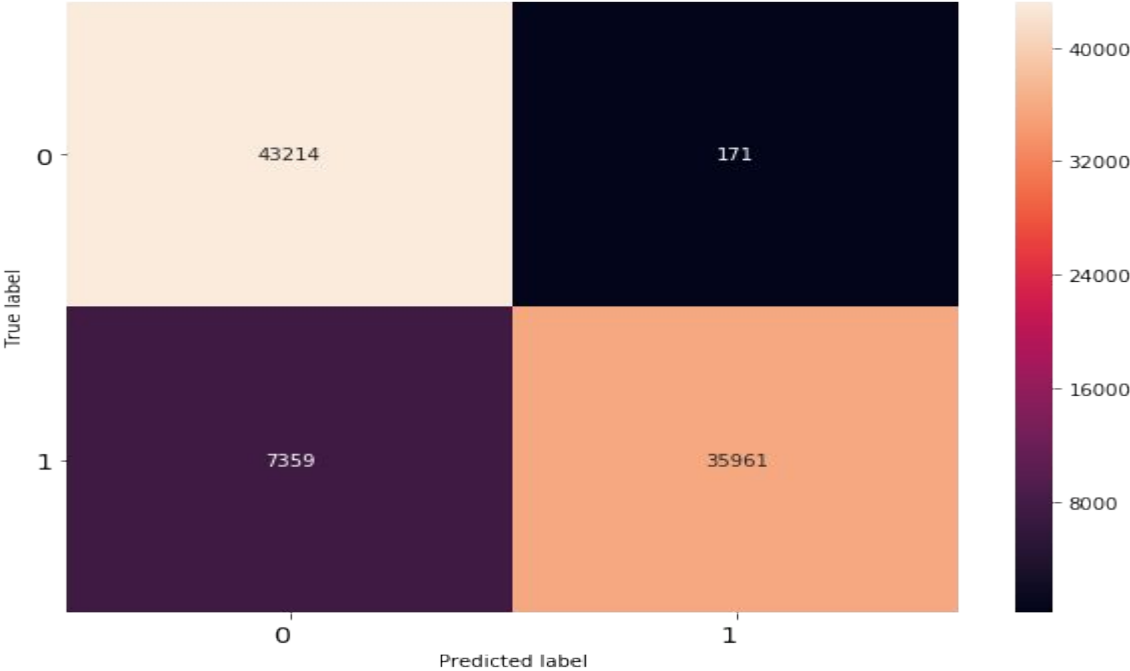
- **Logistic Regression: Train/Test score: 91%, 91%**

	precision	recall	f1-score	support
0	0.85	1.00	0.92	43385
1	1.00	0.83	0.91	43320
accuracy			0.91	86705
macro avg	0.92	0.91	0.91	86705
weighted avg	0.92	0.91	0.91	86705

- **Random Forest: Train/Test Scores: 96%,92%**

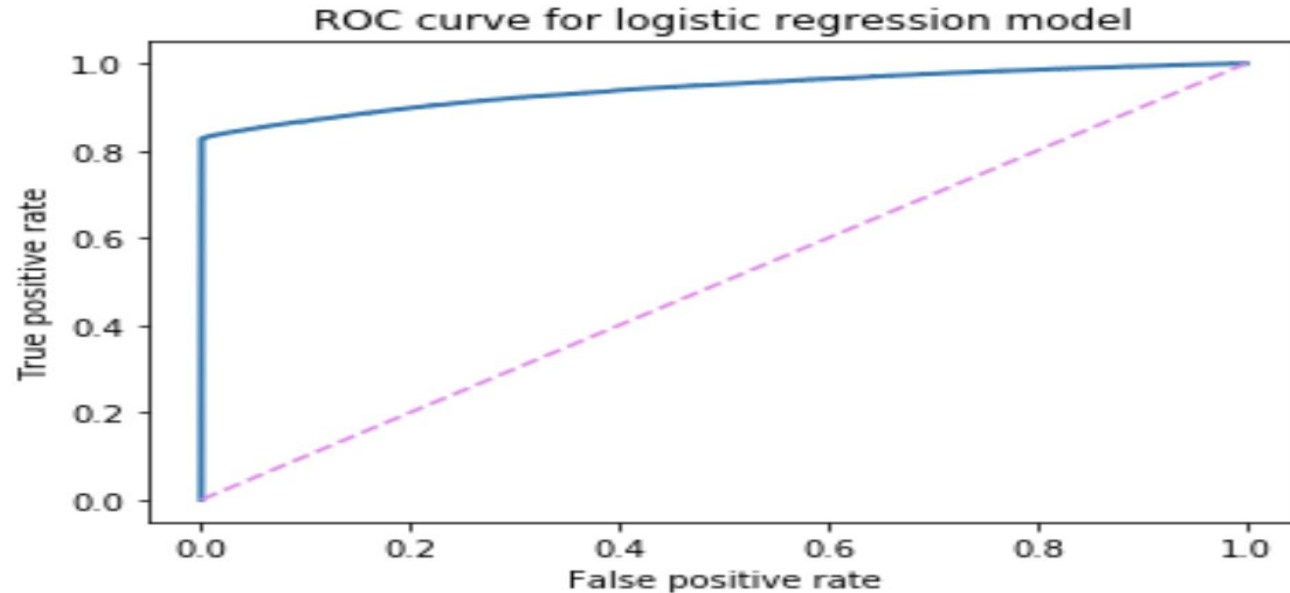
	precision	recall	f1-score	support
0	0.87	0.99	0.93	43385
1	0.99	0.85	0.91	43320
accuracy			0.92	86705
macro avg	0.93	0.92	0.92	86705
weighted avg	0.93	0.92	0.92	86705

Results from Logistic Regression

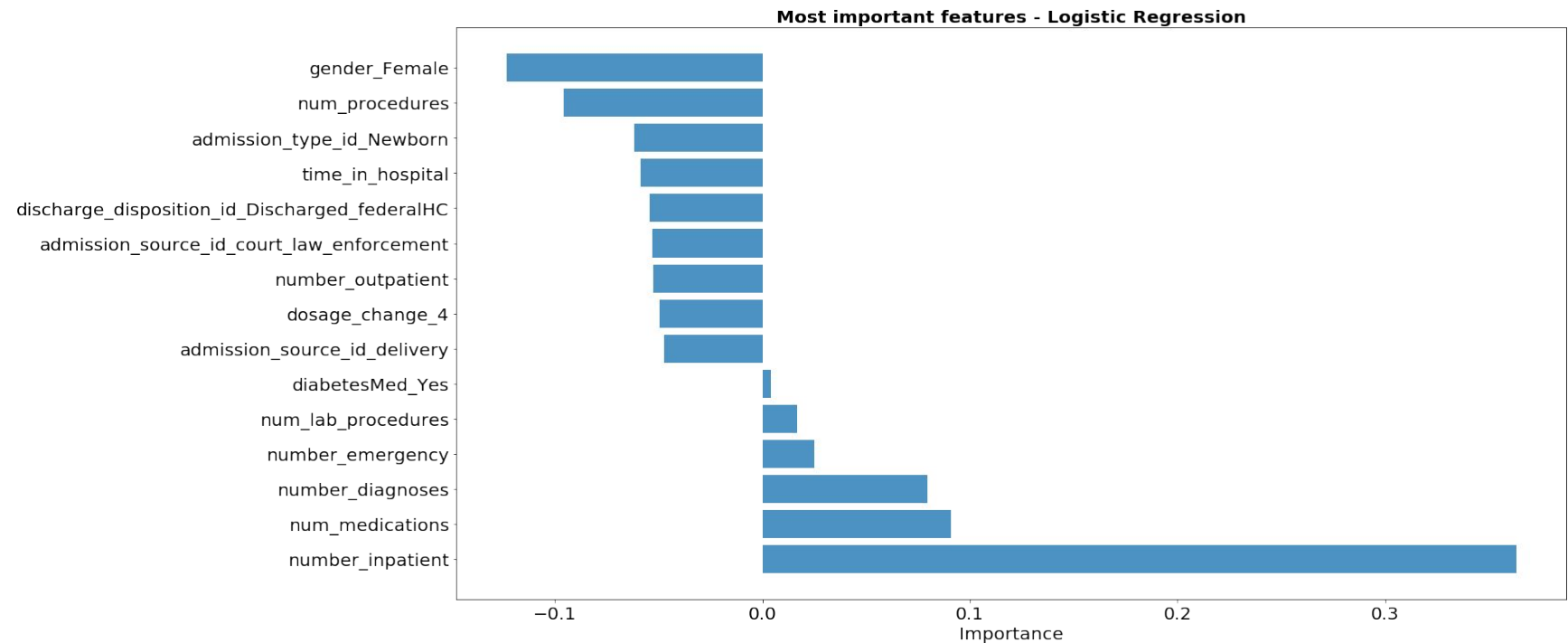


Results from Logistic Regression

ROC AUC score = 0.941605776662409



Results from Logistic Regression

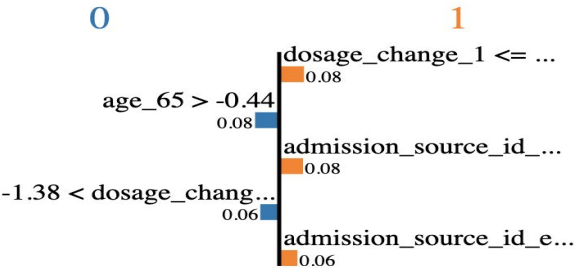
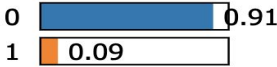


LIME example



```
exp_final = explainer_log_final.explain_instance(x_test_final[10], predict_logistic_final, num_
exp_final.show_in_notebook(show_table = True, show_all=False)
```

Prediction probabilities



Feature Value

dosage_change_1	-0.53
age_65	2.30
admission_source_id_referral	-0.56
dosage_change_0	0.72
admission_source_id_emergency	-1.07

Future Work



- Include the medications and diagnoses relationships in my model (Academic publications available)
- Do more interaction terms and feature engineering



Thank you!