California Wildfires: Predicting Wildfire Spread Using Machine Learning

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Introduction

- **4 million** acres burned, 2020
- **2.6 million** acres burned, 2021
- **$148.5 billion** in costs, 2018
- **30%** emissions increase, 2020
- **50,000** premature deaths, 2008-18

McKinney Fire in Klamath National Forest, CA. (CNN, 2022)

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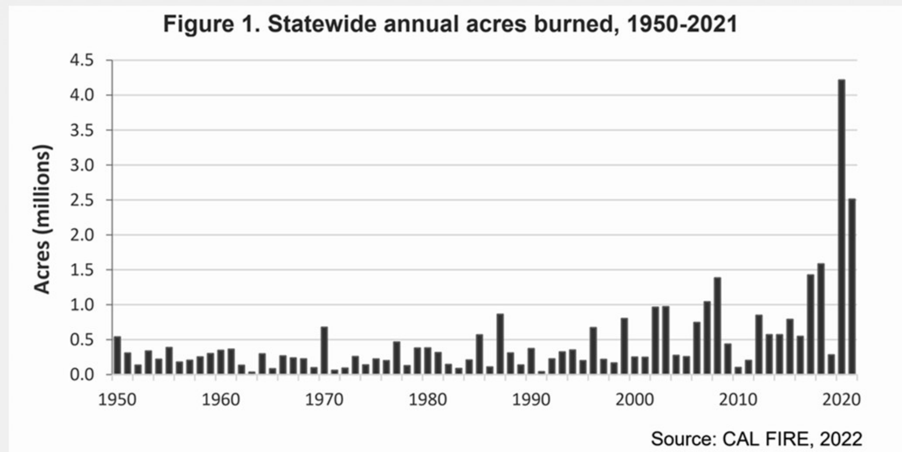
Previous Work


Environmental Impact Assessment Review

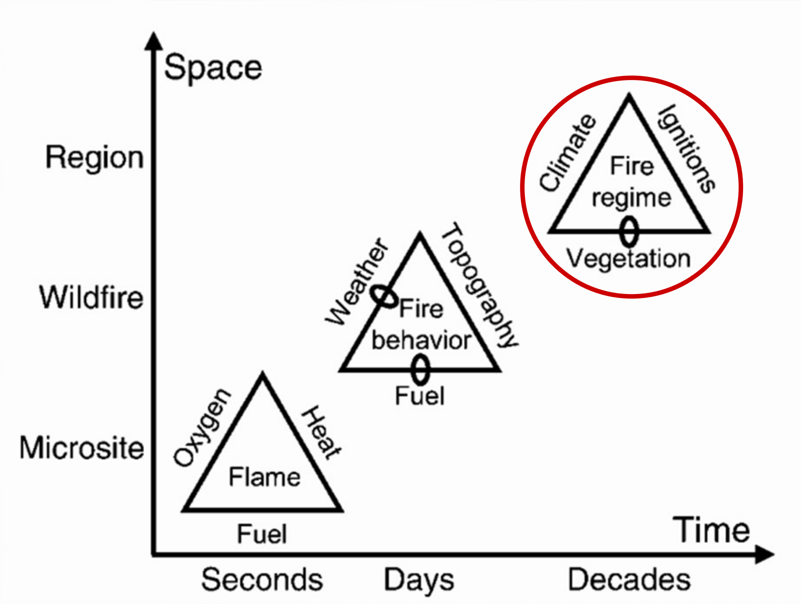
Estimating the probability of wildfire occurrence in Mediterranean landscapes using Artificial Neural Networks

Climate change and the eco-hydrology of fire: Will area burned increase in a warming western USA?



Acreage burned by year. (OEHHA, 2022)

Purpose



Spatial and temporal scales. (Parisien & Moritz, 2009)

Ignition vs. Spread

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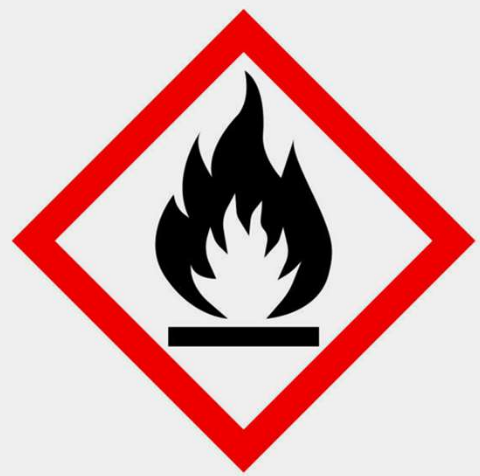
Objective

Determine the flammability of California's landscapes by predicting whether fire will spread given an ignition occurs at a specified time and location.



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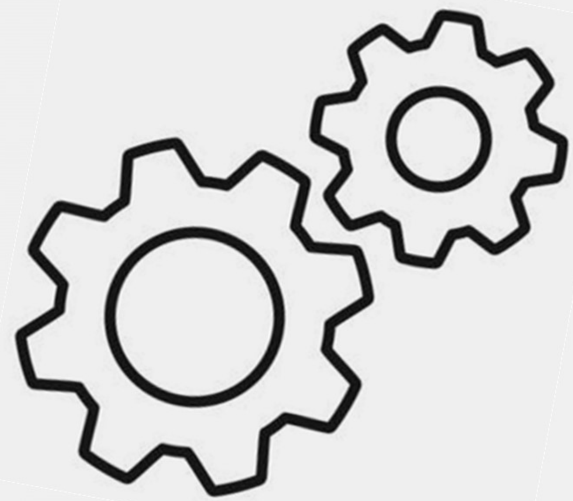
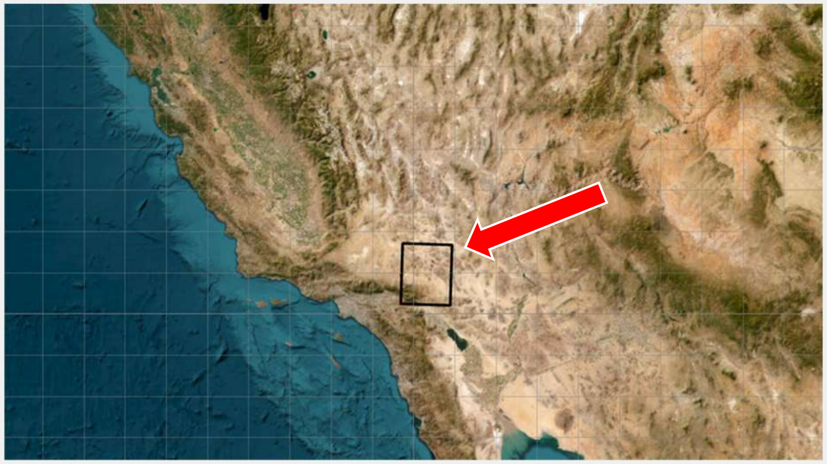
Procedure

- Data Processing
- Time Series Analysis
- Logistic Regression
- Neural Network



Data Sources

- TerraClimate
- Spatial wildfire occurrence data for the United States
- California Vegetation - WHR13 Types



Region of study, California, USA.

Data Description

- ➔ Actual Evapotranspiration
- ➔ Climate Water Deficit
- ➔ Potential Evapotranspiration
- ➔ Precipitation
- ➔ Runoff
- ➔ Soil Moisture
- ➔ Downward Surface Shortwave Radiation
- ➔ Maximum Temperature
- ➔ Minimum Temperature
- ➔ Vapor Pressure
- ➔ Wind Speed
- ➔ Vapor Pressure Deficit
- ➔ Palmer Drought Severity Index

Original observation

Difference

Anomaly

Anomaly Lags

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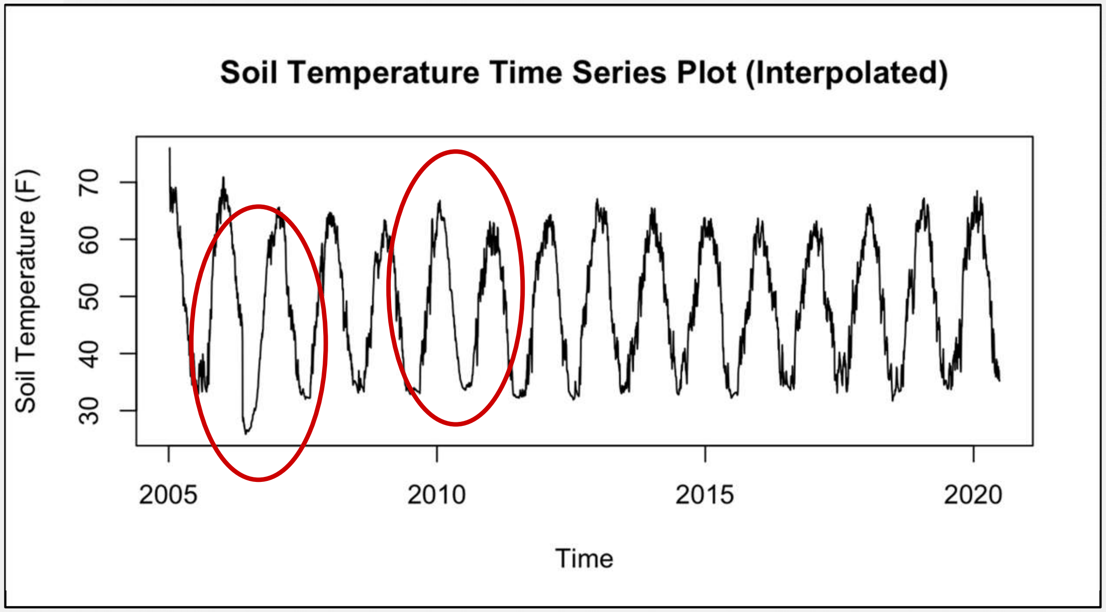
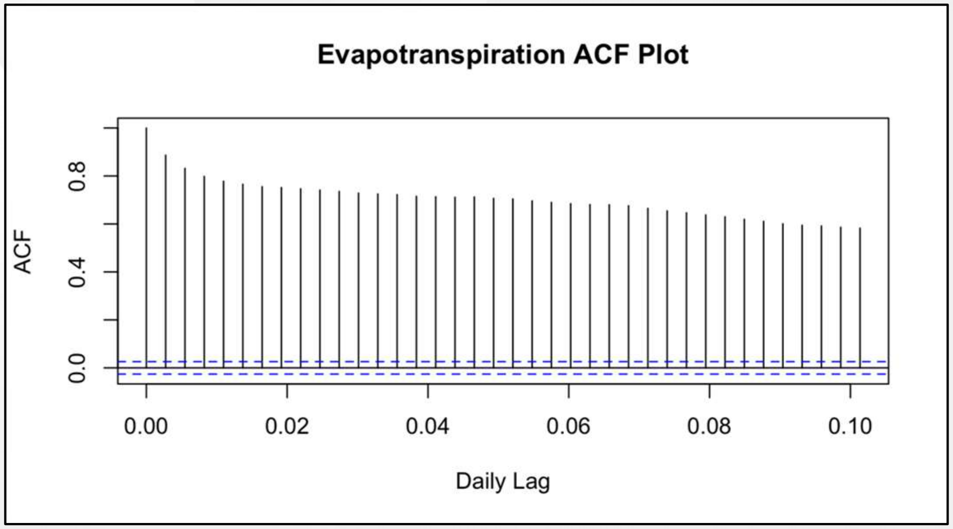
Time Series Analysis

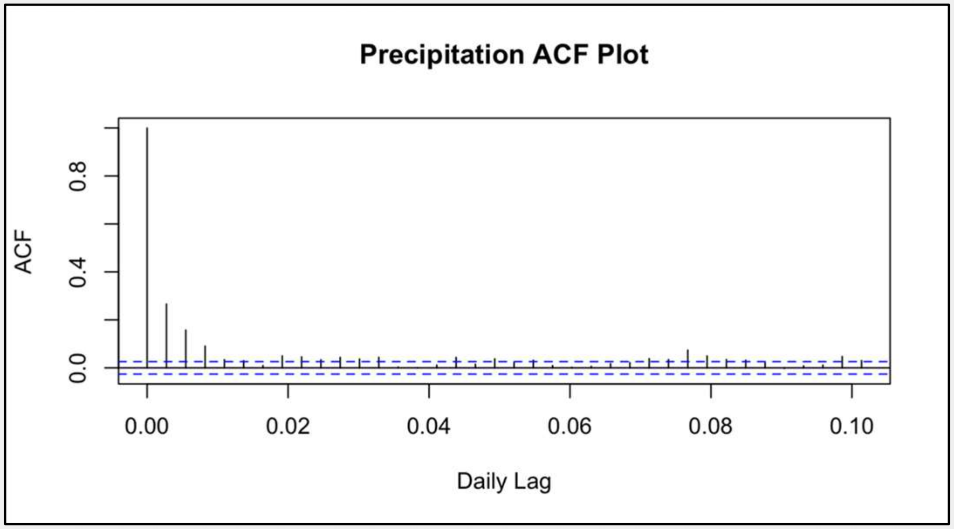
- California Irrigation Management Information System (CIMIS) data



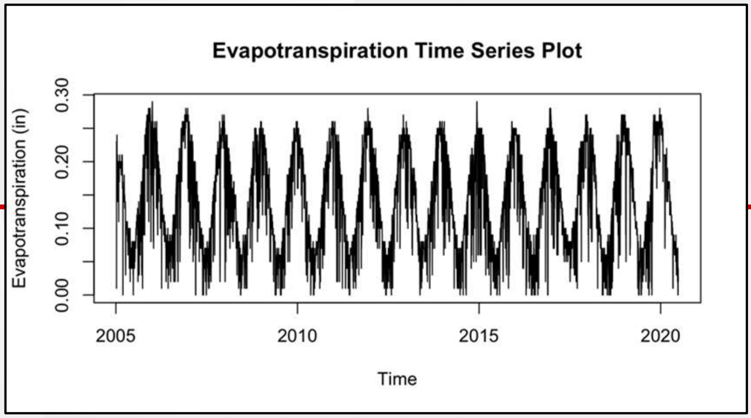
Time Series Analysis Cont.

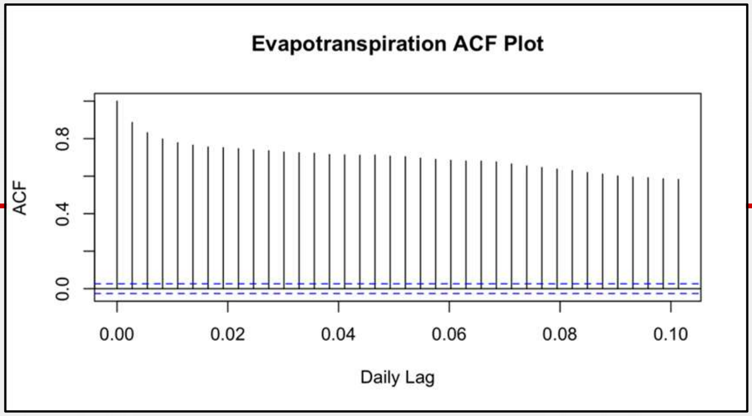
- Checking for stationarity

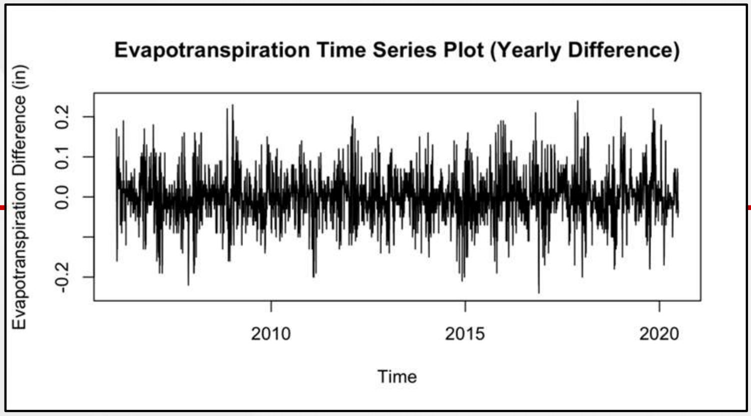


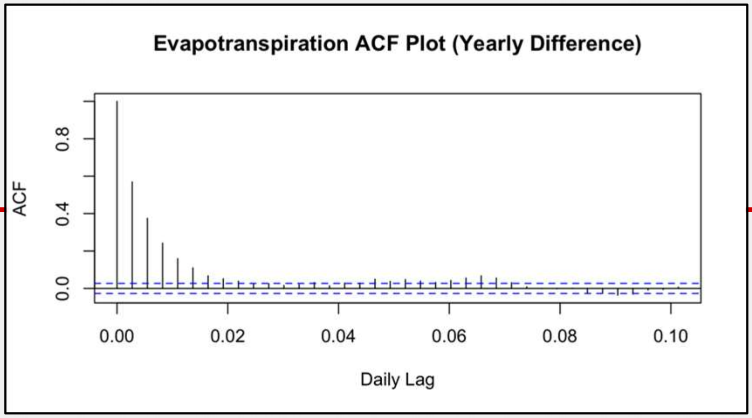


Time Series Analysis Cont.









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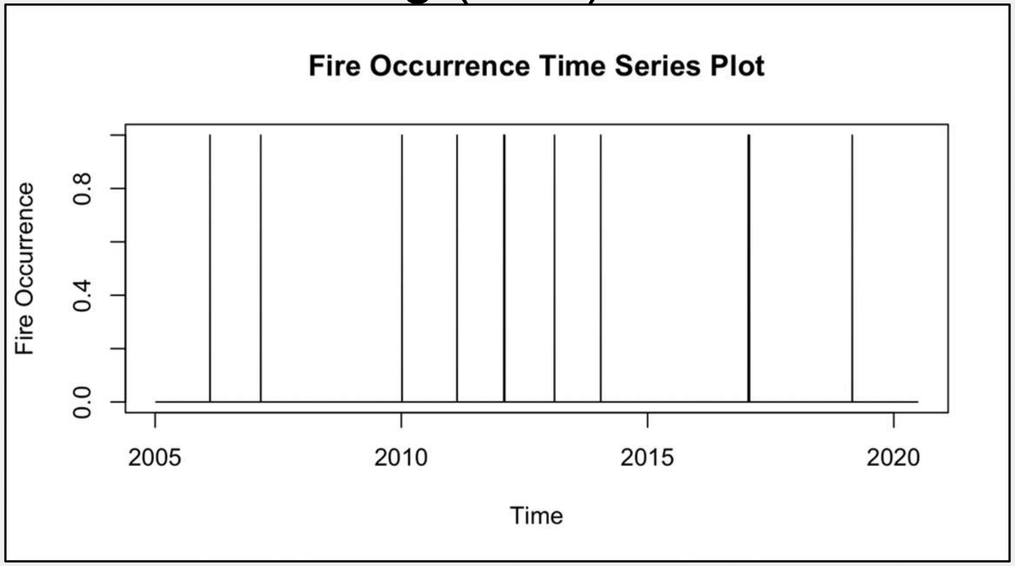
Time Series Analysis Cont.

- Autoregressive (AR) model
- Autoregressive Distributed Lag (ADL) model



Feature Reduction

x_1

⋮

$x_{n\text{-}1}$

x_n

$$\log_e \frac{p}{1-p} = \beta_0 + \beta_1 x_1$$

Keep
($p \leq 0.05$)

Remove
($p > 0.05$)

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Feature Reduction Cont.

Univariate Logistic Regression

LARGE SET

stepAIC

SMALL SET

Feature Reduction Cont.

LARGE SET

↓

Subset

↓

Train-Test Split

SMALL SET

↓

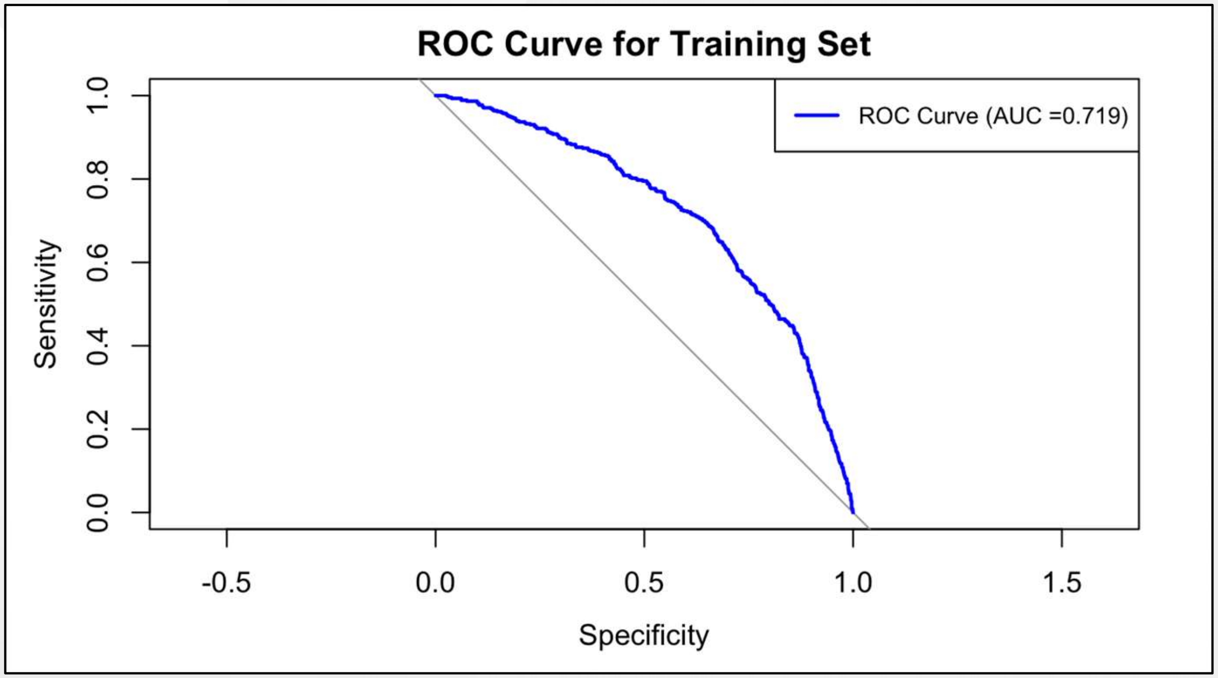
Subset

↓

Train-Test Split

Logistic Regression

Large Variable Set

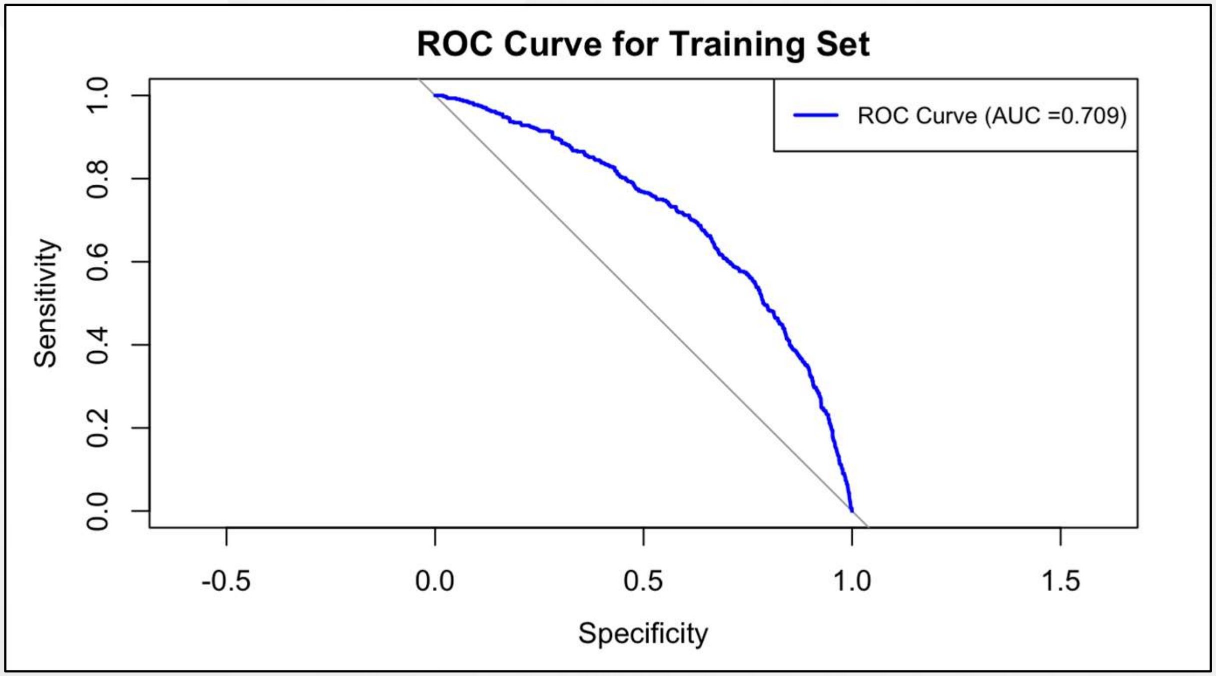


Accuracy	**0.633**
Sensitivity	**0.612**
Specificity	**0.653**
AUC	**0.719**

Optimal Cutoff: 0.214

Logistic Regression Cont.

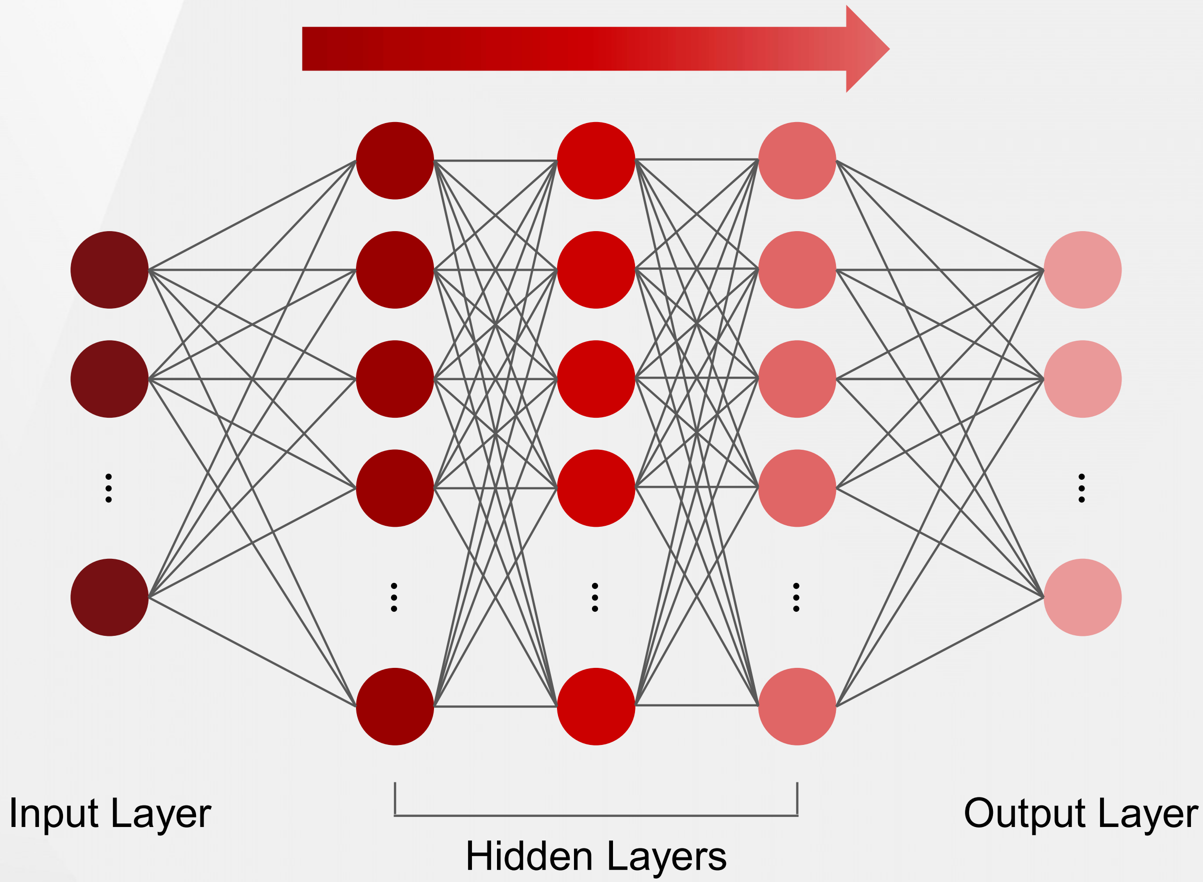
Small Variable Set



Accuracy	**0.643**
Sensitivity	**0.674**
Specificity	**0.612**
AUC	**0.709**

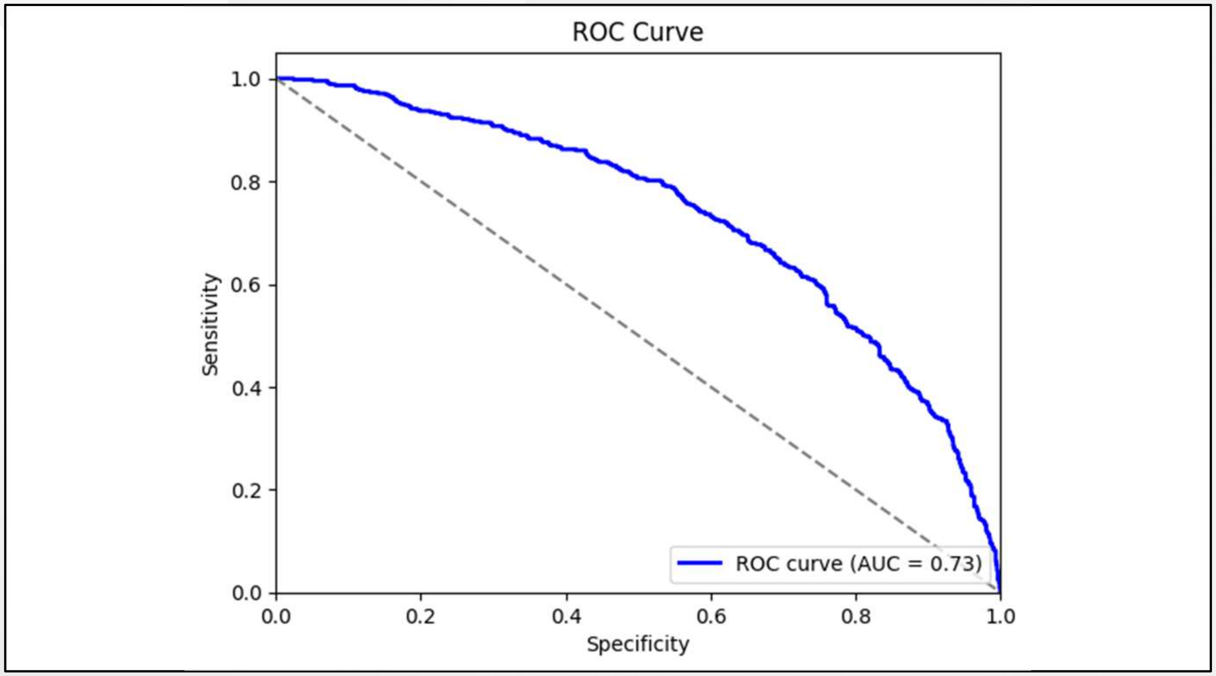
Optimal Cutoff: 0.203

Feed-Forward Neural Network



Feed-Forward Neural Network Cont.

Large Variable Set

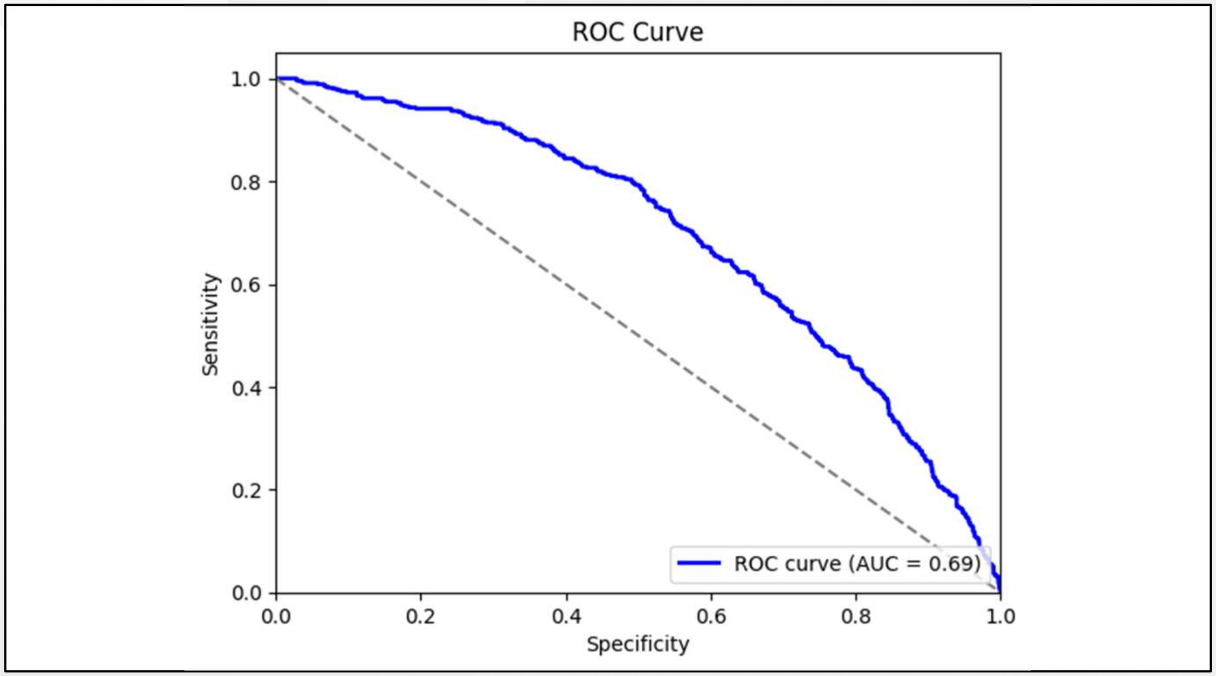


Accuracy	**0.740**
Sensitivity	**0.640**
Specificity	**0.840**
AUC	**0.733**

Optimal Cutoff: 0.398

Feed-Forward Neural Network Cont.

Small Variable Set



Accuracy	**0.680**
Sensitivity	**0.800**
Specificity	**0.560**
AUC	**0.691**

Optimal Cutoff: 0.335

Results

	Large Logistic	Small Logistic	Large NN	Small NN
Accuracy	0.633	0.643	**0.740**	0.680
Sensitivity	0.612	0.674	0.640	**0.800**
Specificity	0.653	0.612	**0.840**	0.560
AUC	0.719	0.709	**0.733**	0.691

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Discussion


Strong winds. (Delbert, 2022)


Former wetland near Tulelake, California. (NPR, 2022)

Conclusion

- *Summary*
  - Neural networks outperformed logistic regression models
  - Subset approach disregards time series element
- *Future work*
  - Other neural networks
  - New variable combinations and selection methods
  - Need for complementary ignition model

Fighting a wildfire. (WHO, 2024)

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Thank you!

Questions?

References

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Data

-12 months for 29 years; 348 months; Jan 1992-Dec 2020

-217,500 total rows of observations (348 x 625)

-25x25 region = 625 cells (16 km^2)

-region with habitat variability; has enough fires to be relevant to study

-near LA and important parks

:)

aet: (Actual Evapotranspiration, monthly total), units = mm   water leaving soil
def: (Climate Water Deficit, monthly total), units = mm   pet minus aet
pet: (Potential evapotranspiration, monthly total), units = mm   water could transpire
ppt: (Precipitation, monthly total), units = mm
q: (Runoff, monthly total), units = mm   not absorbed by soil
soil: (Soil Moisture, total column - at end of month), units = mm   water in soil
srad: (Downward surface shortwave radiation), units = W/m2   sunlight
tmax: (Max Temperature, average for month), units = C
tmin: (Min Temperature, average for month), units = C
vap: (Vapor pressure, average for month), units = kPa   humidity
ws: (Wind speed, average for month), units = m/s
vpd: (Vapor Pressure Deficit, average for month), units = kpa   dryness
PDSI: (Palmer Drought Severity Index, at end of month), units = unitless   neg=dry
fires: total number of fires, count
fire_total: sum of fire area in given month and given cell
habitat: specific habitat classification (most common specific habitat in that cell)
habitat_g: general habitat classification (most common general habitat in that cell)
cell: concatenated lon0 and lat0 with comma separator
fire_events: 1 when at least one natural fire; 0 when no natural fire
fire_spread: 1 when fire area >0.1 acres; 0 when smaller or none

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Logistic including lag anomalies

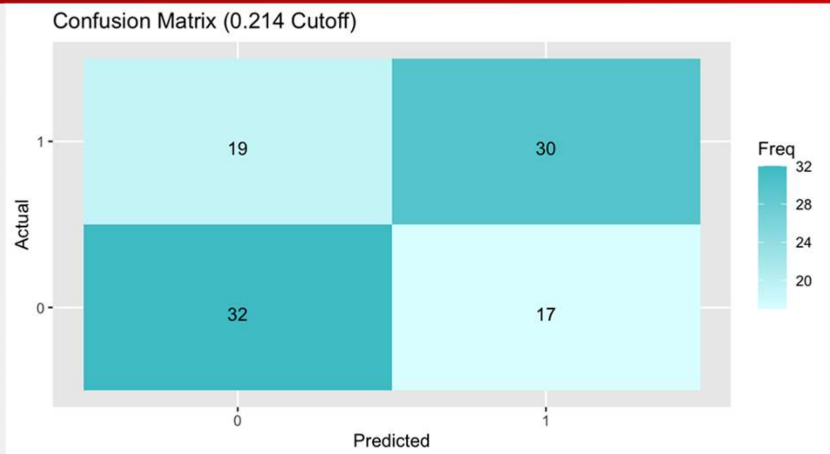
-90-10 train-test split
-all variables; reduce based on p-val >0.05
-remove:
#"q"
#"diff_aet"
#"diff_ppt"
#"diff_q"
#"diff_soil"
#"diff_PDSI"
#"anom_q"
#"anom_srad"
#"lag_anom_srad"
-reduce with stepAIC to:
#Step: AIC=2028.84
aet + def + ppt + srad + vap + ws + vpd + PDSI + diff_pet + diff_tmin + diff_vap + diff_vpd + anom_aet + anom_def + anom_pet + anom_ppt + anom_vap + anom_ws + anom_vpd + anom_PDSI + lag_anom_def + lag_anom_pet + lag_anom_vap
-optcutoff on train data;
confusion/accuracy/pred for test data

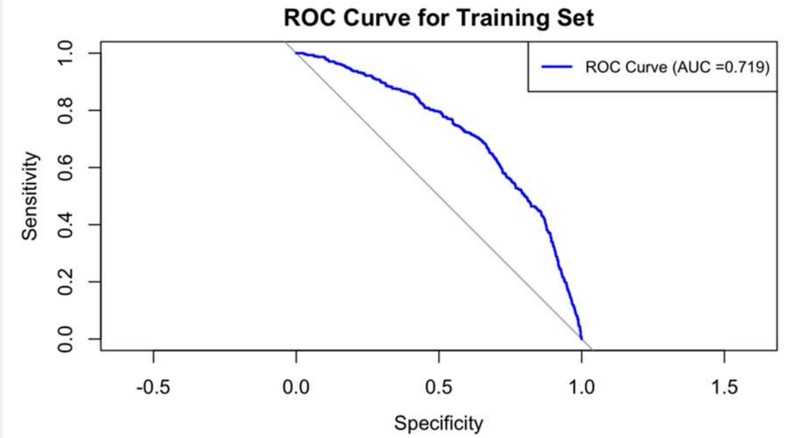
-STEP model has higher accuracy, sensitivity
-FULL model has higher specificity, AUC

Logistic including lag anomalies (LARGE)

-90-10 train-test split
-all variables; reduce based on p-val >0.05
-remove:
#"q"
#"diff_aet"
#"diff_ppt"
#"diff_q"
#"diff_soil"
#"diff_PDSI"
#"anom_q"
#"anom_srad"
#"lag_anom_srad"

-full model results:
-using optcutoff (YJS): 0.2136121
#Accuracy : 0.6327
#Sensitivity : 0.6122
#Specificity : 0.6531
#AUC : 0.719

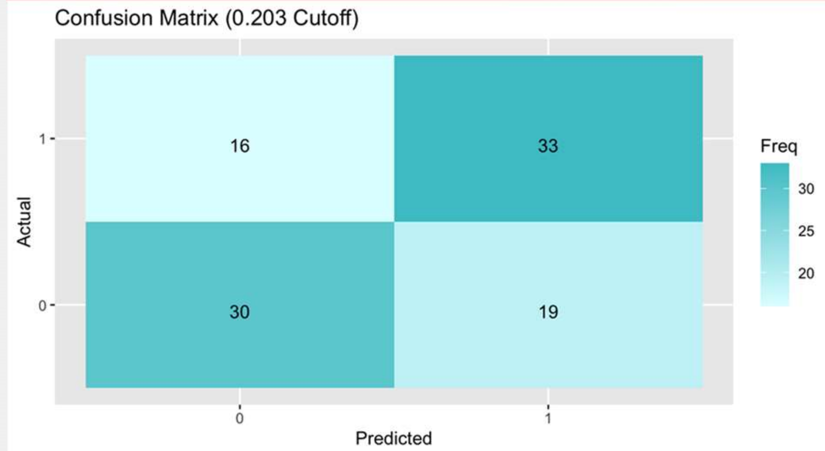


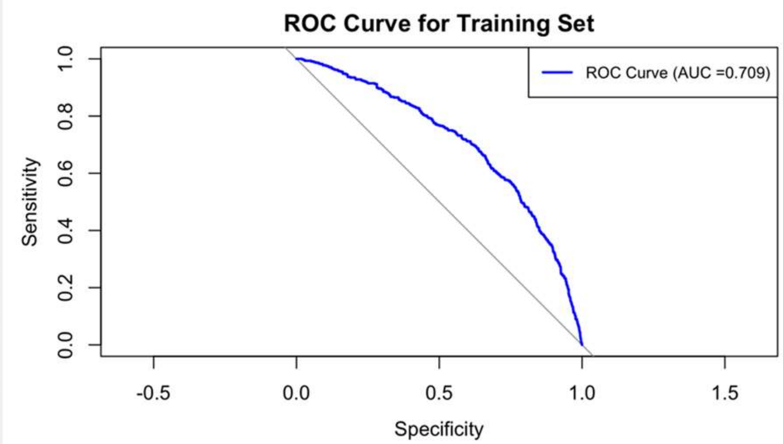


Logistic including lag anomalies (SMALL)

-90-10 train-test split
-all variables; reduce based on p-val >0.05
-remove:
#"q"
#"diff_aet"
#"diff_ppt"
#"diff_q"
#"diff_soil"
#"diff_PDSI"
#"anom_q"
#"anom_srad"
#"lag_anom_srad"
-reduce with stepAIC to:
#Step: AIC=2028.84
aet + def + ppt + srad + vap + ws + vpd + PDSI + diff_pet + diff_tmin + diff_vap + diff_vpd + anom_aet + anom_def + anom_pet + anom_ppt + anom_vap + anom_ws + anom_vpd + anom_PDSI + lag_anom_def + lag_anom_pet + lag_anom_vap
-optcutoff on train data;
confusion/accuracy/pred for test data

-step model results:
-using optcutoff (YJS): 0.2031919
#Accuracy : 0.6429
#Sensitivity : 0.6735
#Specificity : 0.6122
#AUC : 0.709



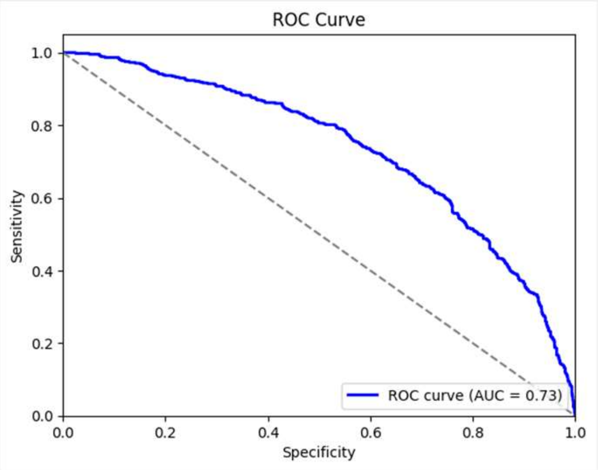


NN including lag anomalies (LARGE)

-90-10 train-test split
-all variables; reduce based on p-val >0.05
-remove:
#"q"
#"diff_aet"
#"diff_ppt"
#"diff_q"
#"diff_soil"
#"diff_PDSI"
#"anom_q"
#"anom_srad"
#"lag_anom_srad"

-activation: leaky_relu
-5 layers: 80, 60, 40, 20, 1
-binary focal cross-entropy (alpha=0.1)
-optimizer: adam
-normalized
-30 epochs, batch size 10

-full model results:
-using optcutoff (YJS): 0.39797372
#Accuracy : 0.740
#Sensitivity : 0.640
#Specificity : 0.840
#AUC : 0.733



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NN including lag anomalies (SMALL)

-90-10 train-test split
-all variables; reduce based on p-val >0.05
-remove:
#"q"
#"diff_aet"
#"diff_ppt"
#"diff_q"
#"diff_soil"
#"diff_PDSI"
#"anom_q"
#"anom_srad"
#"lag_anom_srad"
-ALSO reduce with stepAIC to:
#Step: AIC=2028.84
aet + def + ppt + srad + vap + ws + vpd + PDSI + diff_pet + diff_tmin + diff_vap + diff_vpd + anom_aet + anom_def + anom_pet + anom_ppt + anom_vap + anom_ws + anom_vpd + anom_PDSI + lag_anom_def + lag_anom_pet + lag_anom_vap
-optcutoff on train data;
confusion/accuracy/pred for test data

-full model results:
-using optcutoff (YJS): 0.33526808
#Accuracy : 0.680
#Sensitivity : 0.800
#Specificity : 0.560
#AUC : 0.691

-activation: leaky_relu
-5 layers: 80, 60, 40, 20, 1
-binary focal cross-entropy (alpha=0.1)
-optimizer: adam
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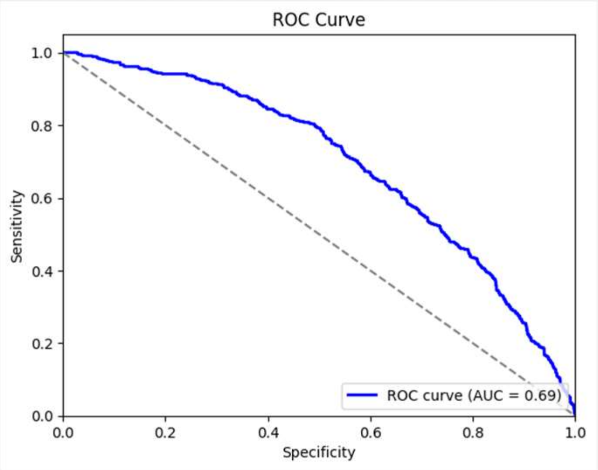

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