What's covering me? - Prediction of forest cover type based on cartographic variables

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The Purpose

- Apply various machine learning techniques

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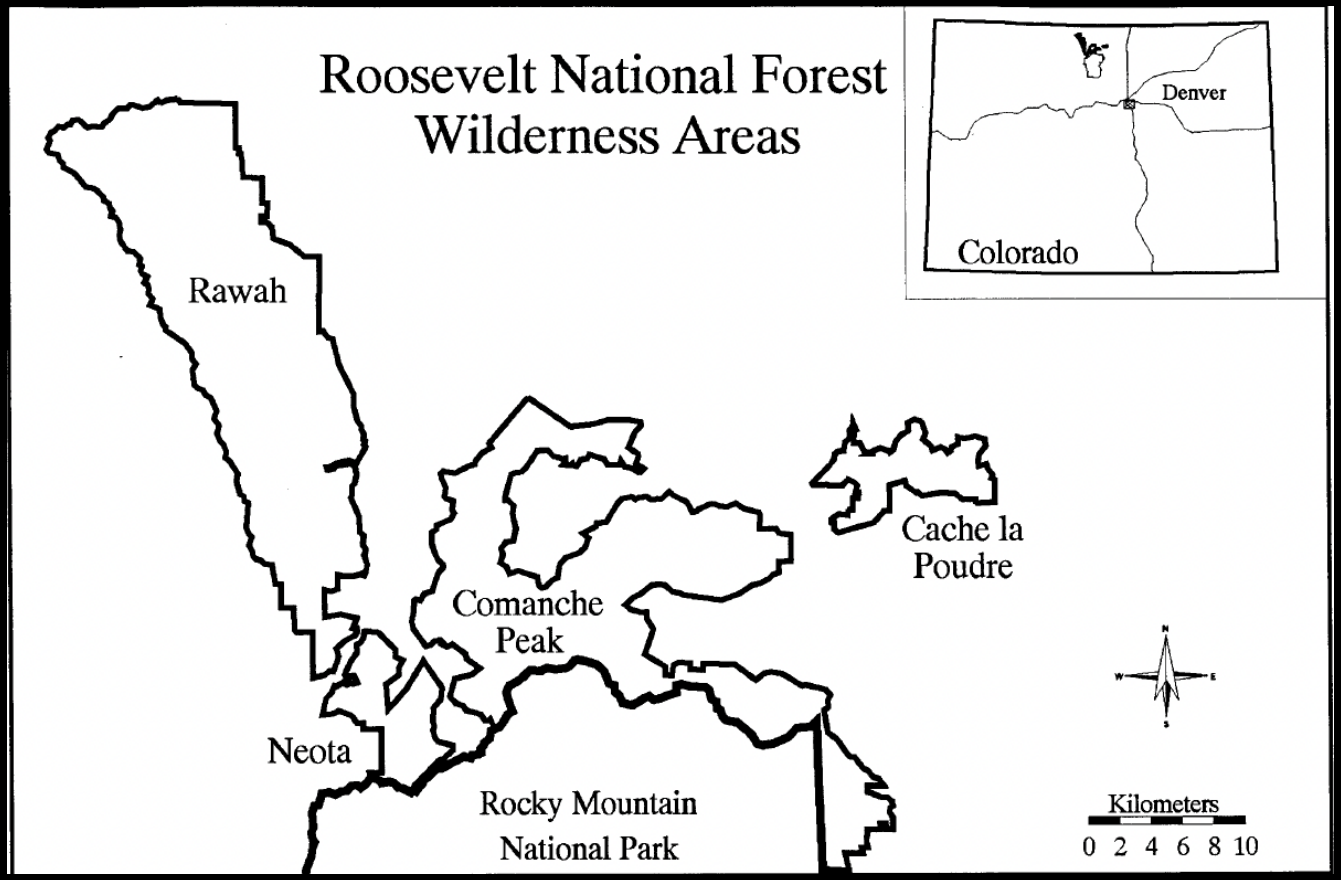
- Apply various machine learning techniques
- Explore ensemble learning

The Data Set

- Cartographic data from four parks
  - Rawah, Comanche Peak, Neota, and Cache la Poudre



The Data Set

Spruce/Fir

Cottonwood/Willow

Krummholz

Lodgepole Pine

Aspen

Ponderosa Pine

Douglas Fir

Predictors of Forest Cover Type:

- Elevation in meters
- Aspect in degrees
- Slope in degrees
- Horz Dist water
- Vert Dist to water
- Horz Dist to roadway
- Hillshade index
- Horz Dist to wildfire
- Wilderness area
- Soil Type

Current Literature

- Blackard and Dean (1999) - Compare neural network and discriminant analyses.

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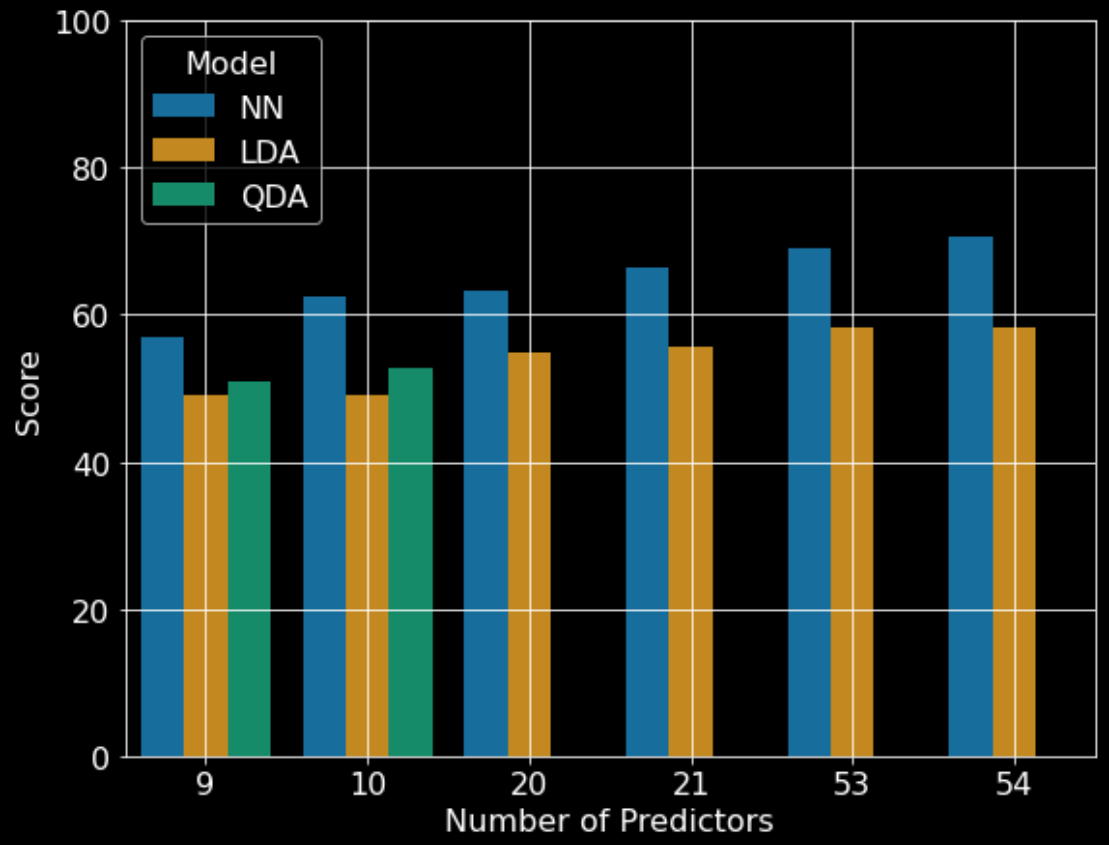

Current Literature

- Oza and Russell (2001)
  - Used ensemble learning
  - Reports effective

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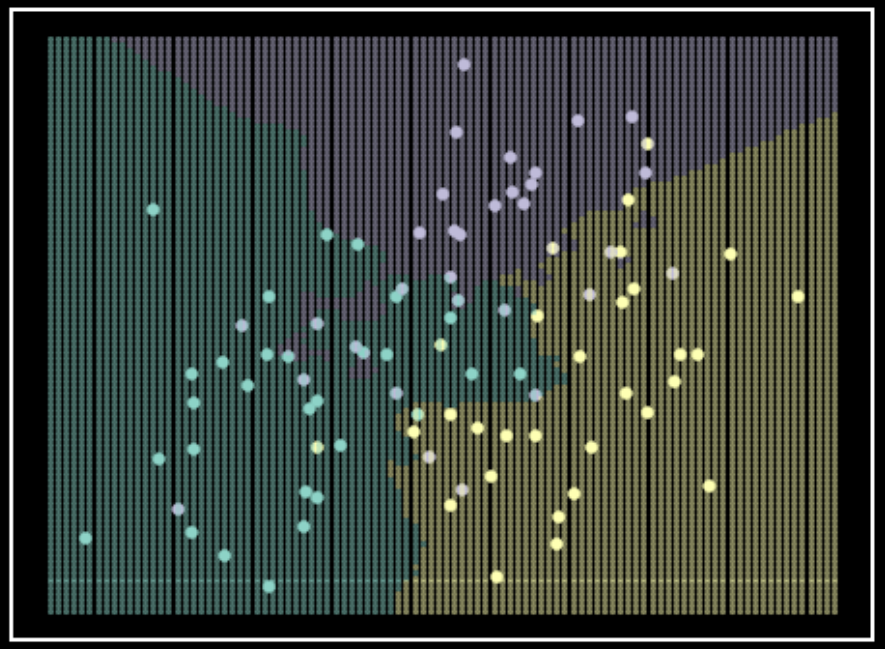

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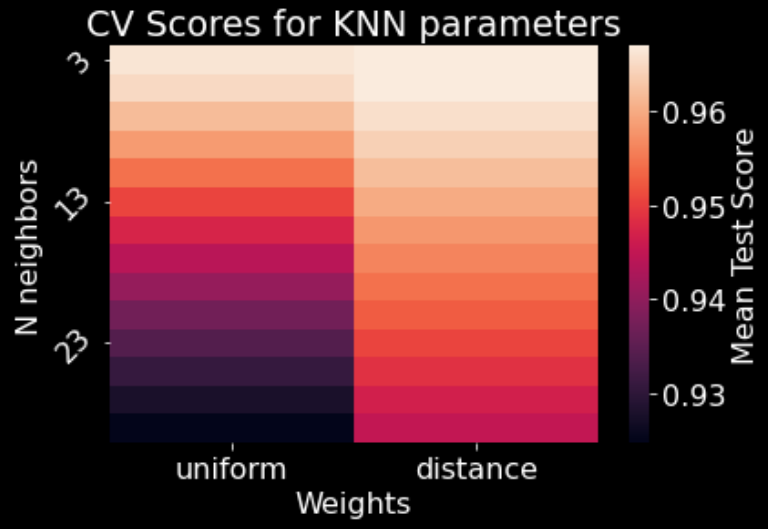

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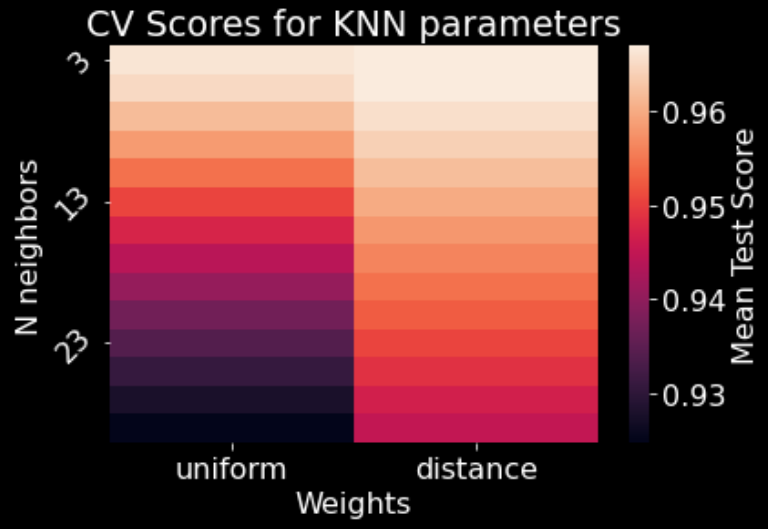

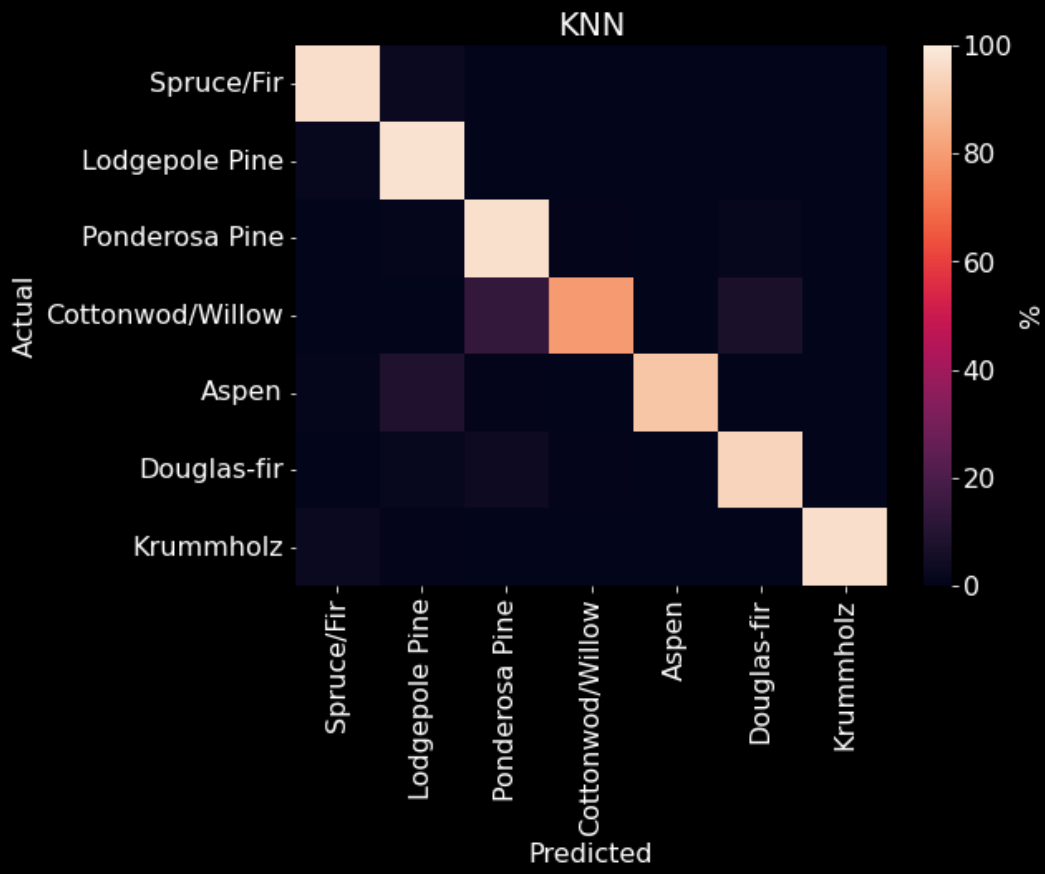

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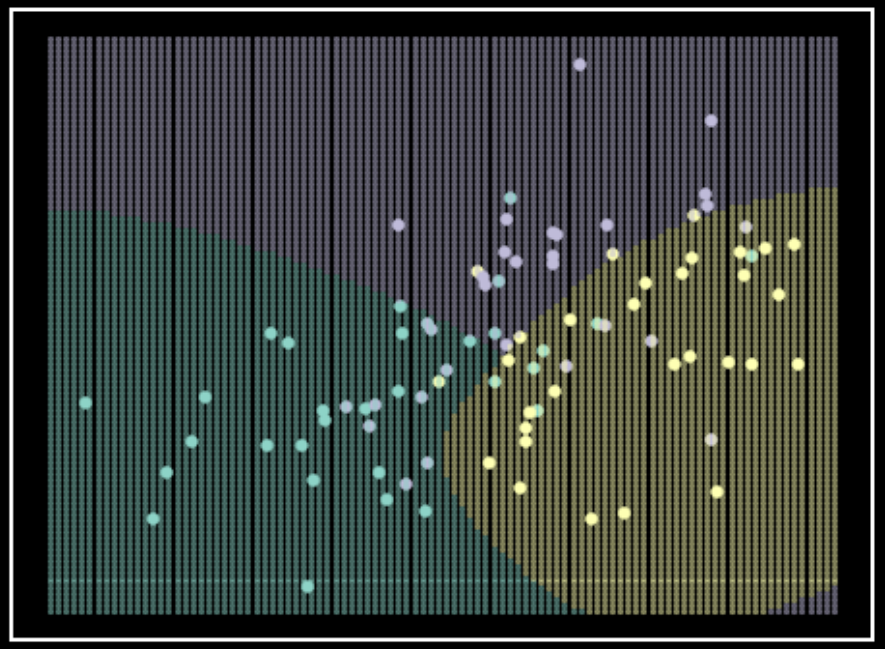

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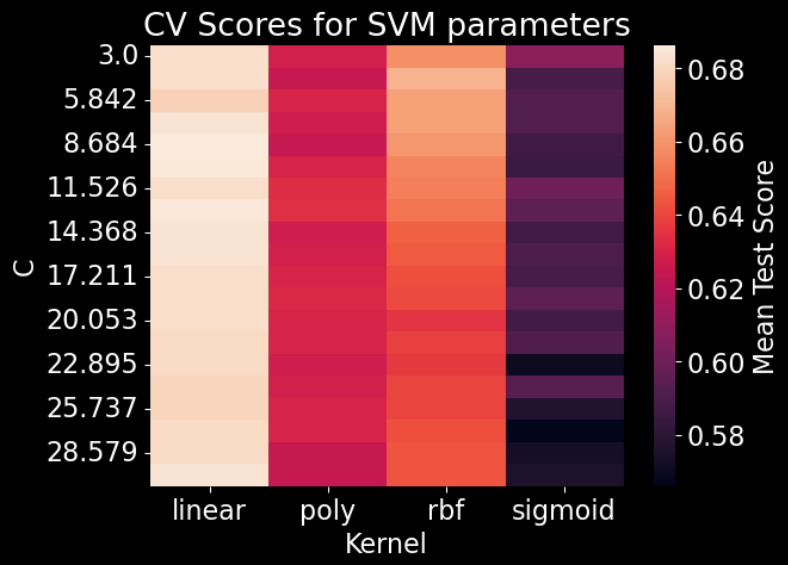

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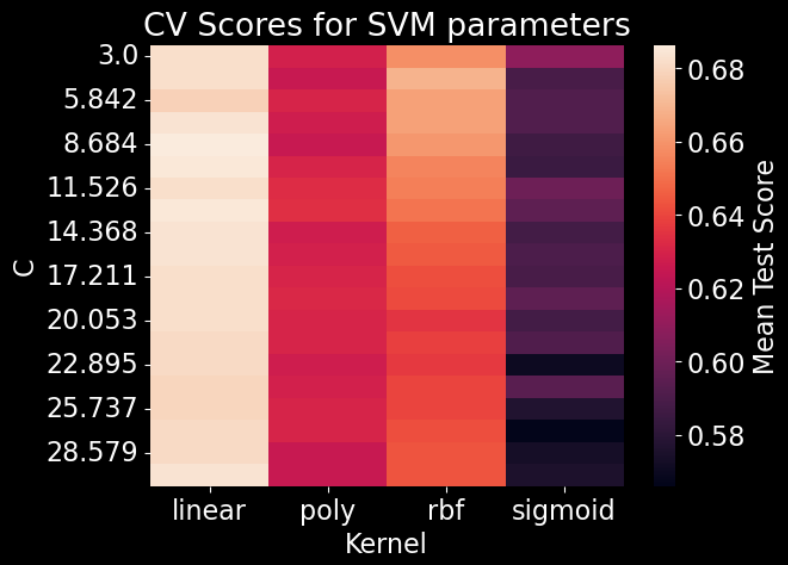

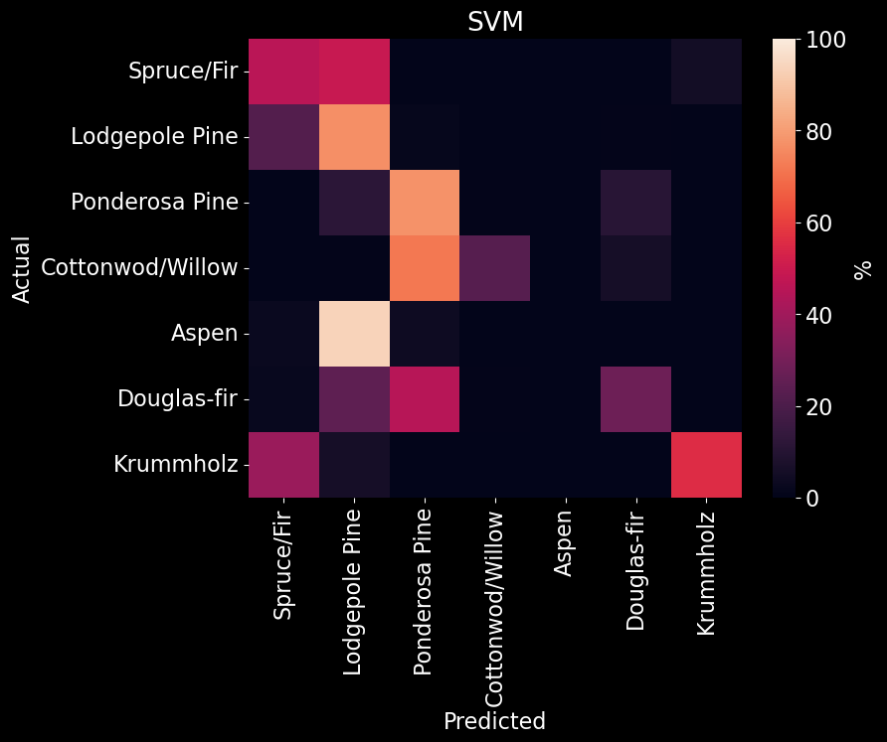

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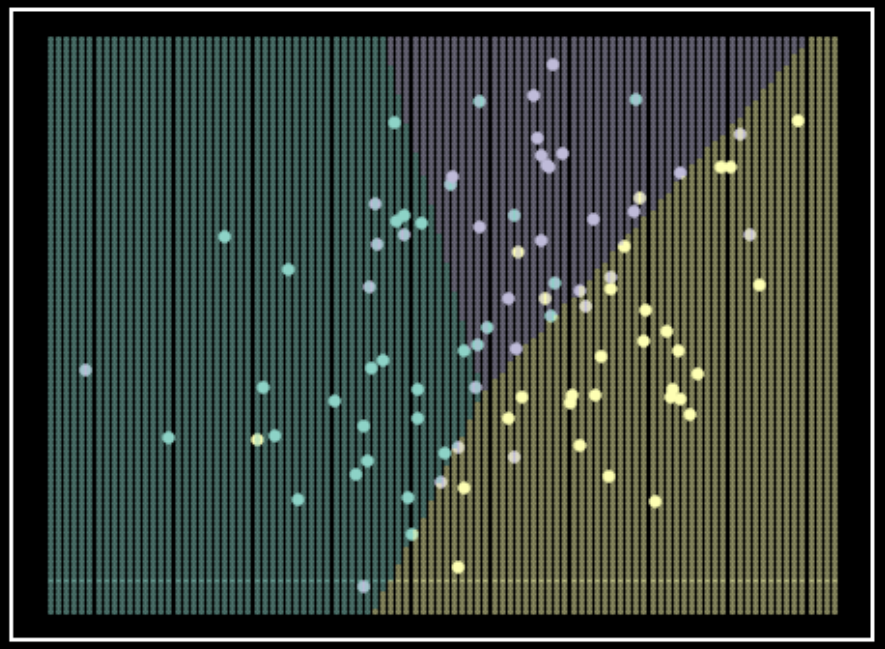

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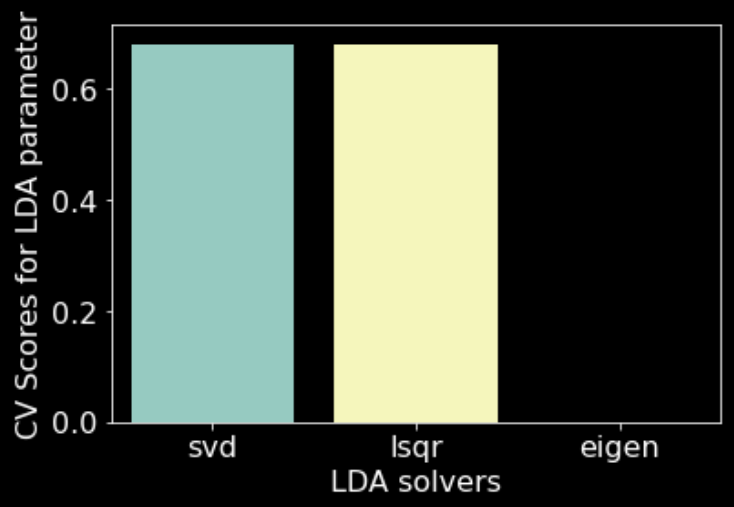

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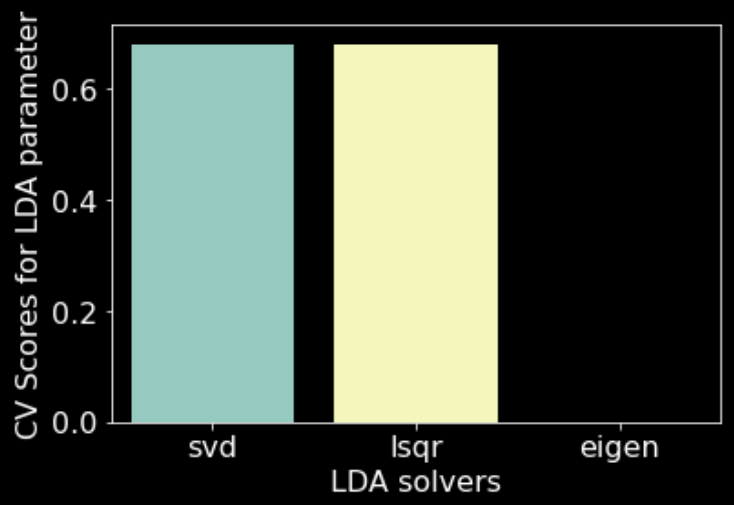

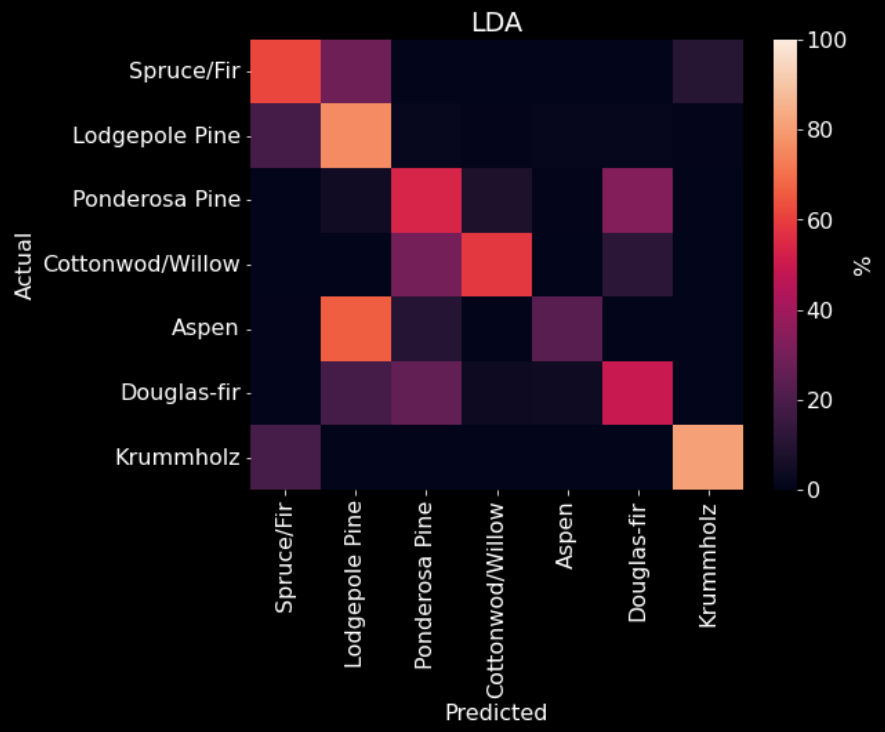

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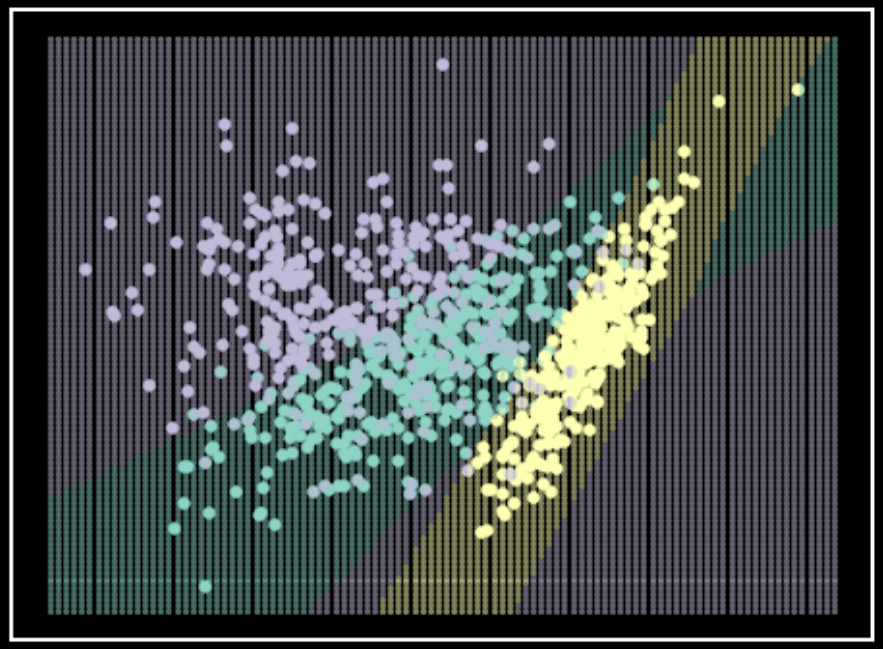

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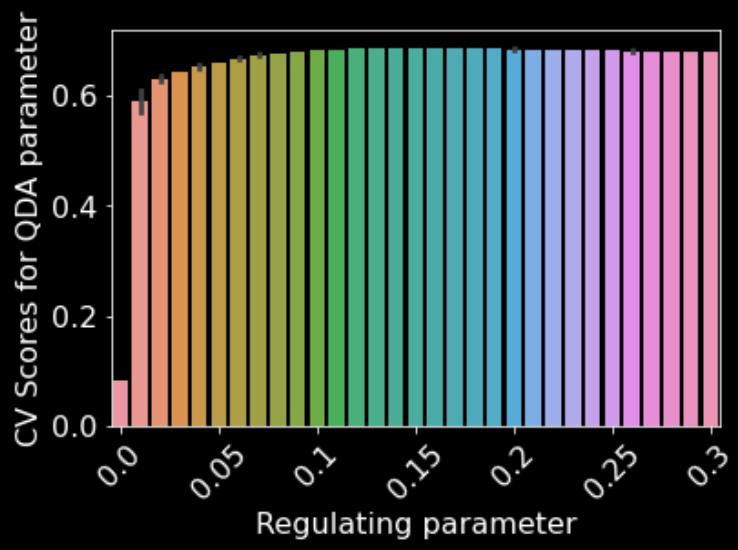

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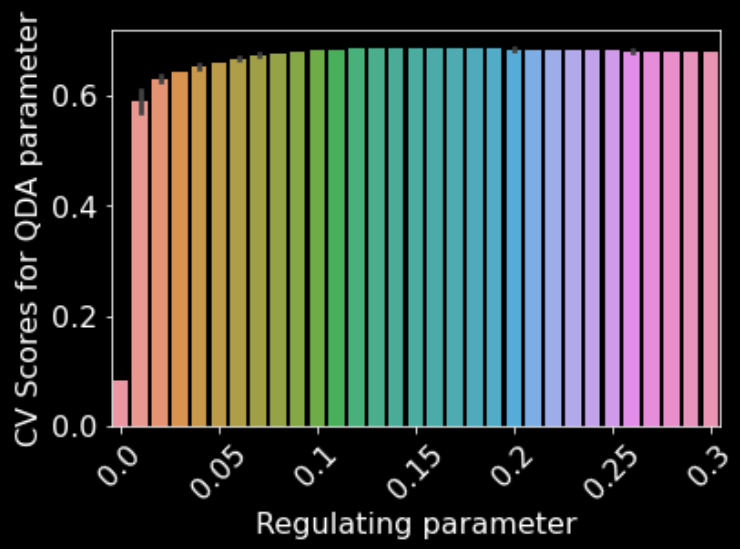

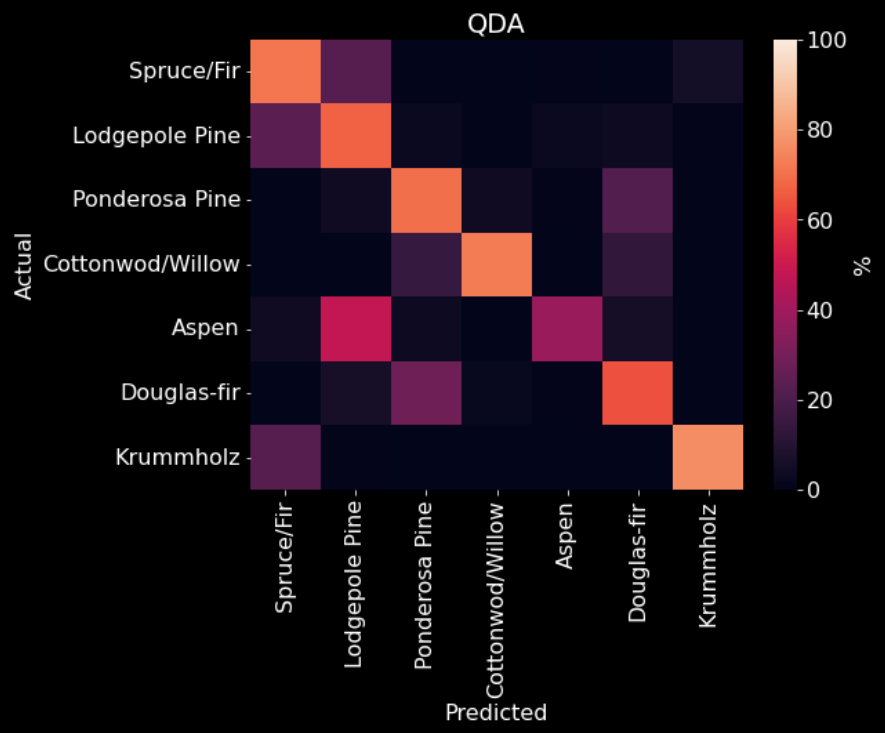

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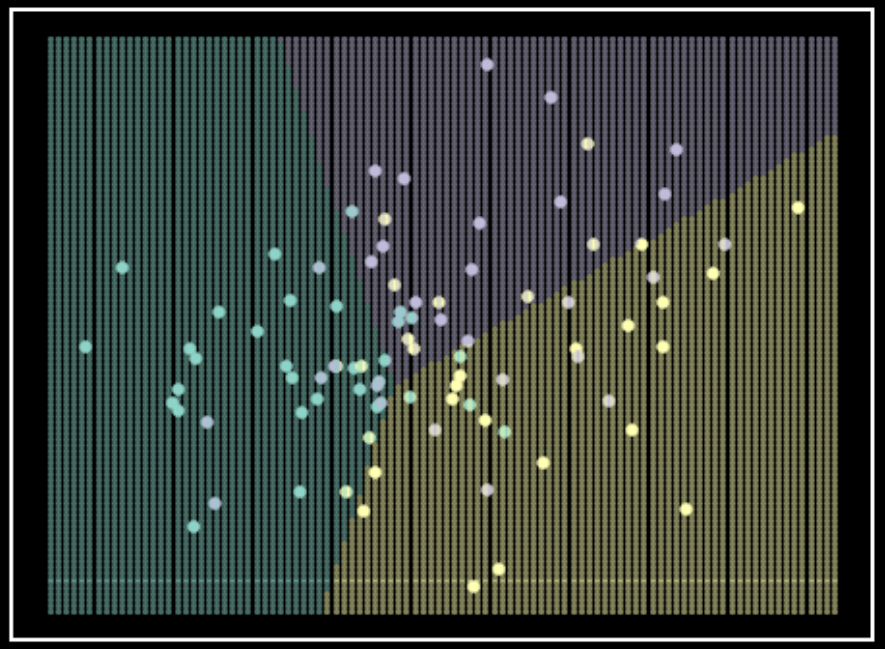

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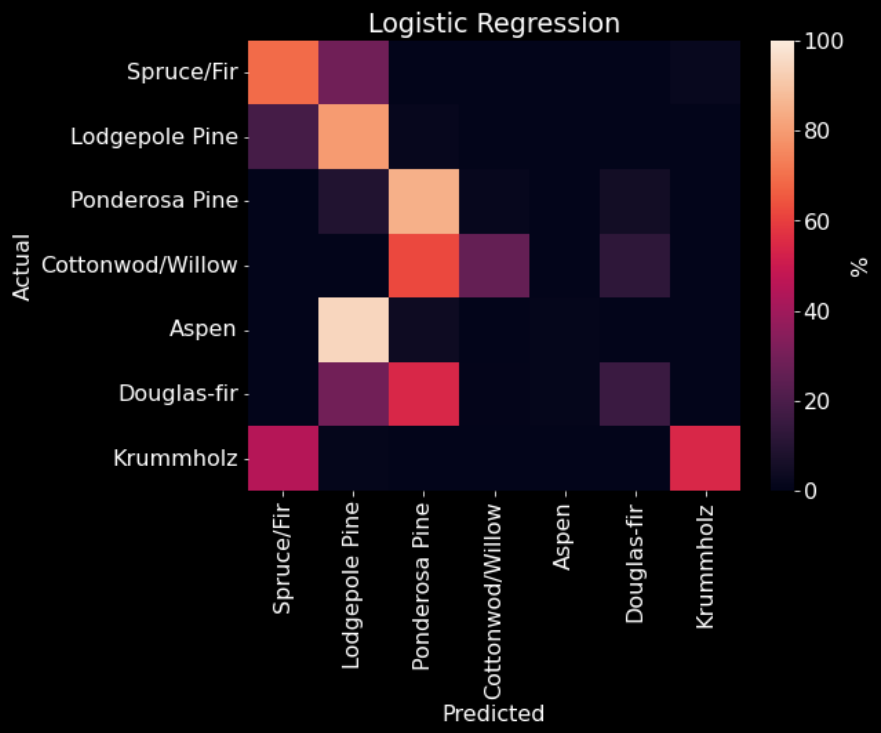

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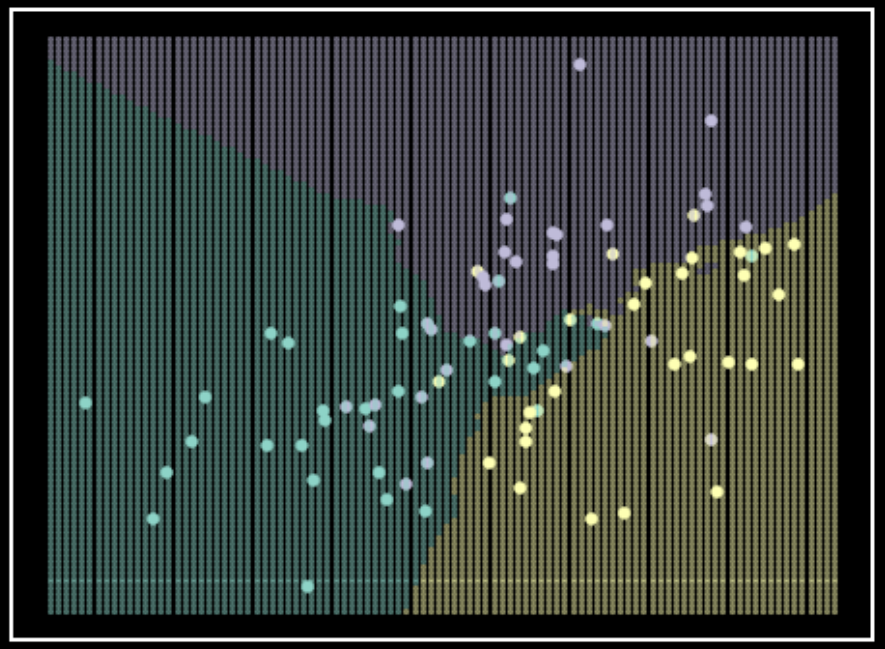

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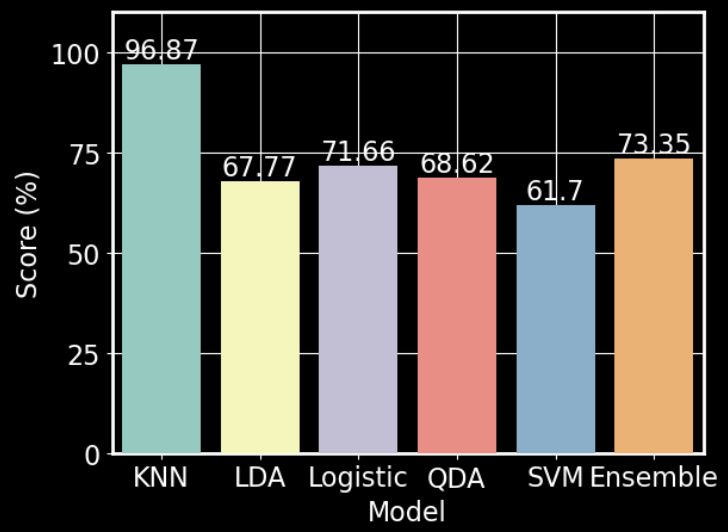

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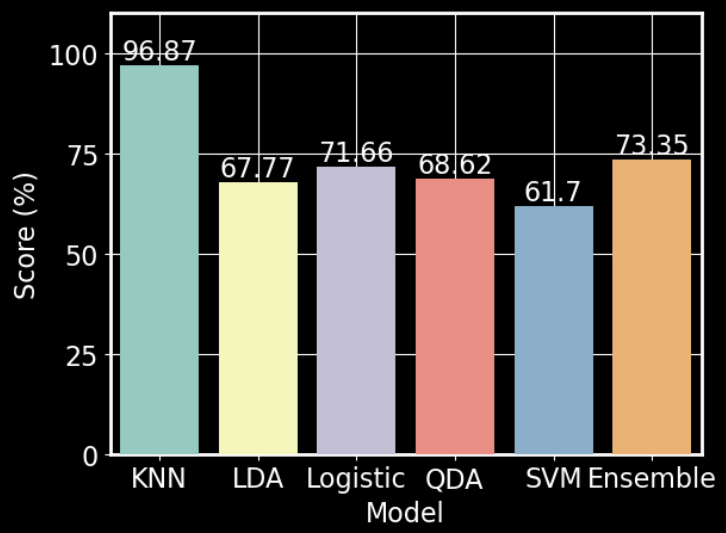

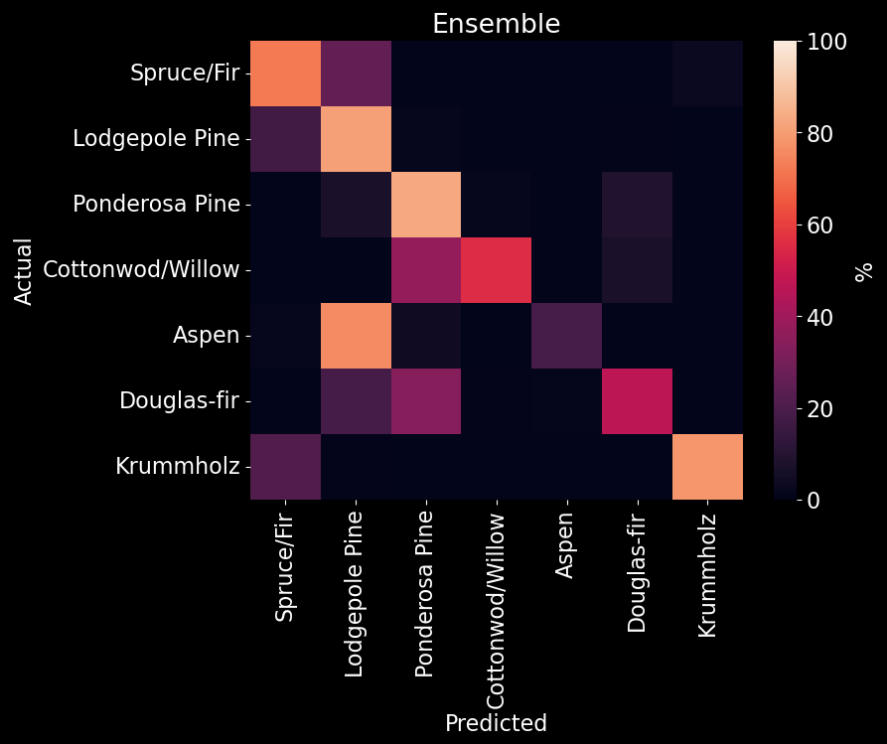

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