# Crop Classification with Multi-Temporal Satellite Imagery

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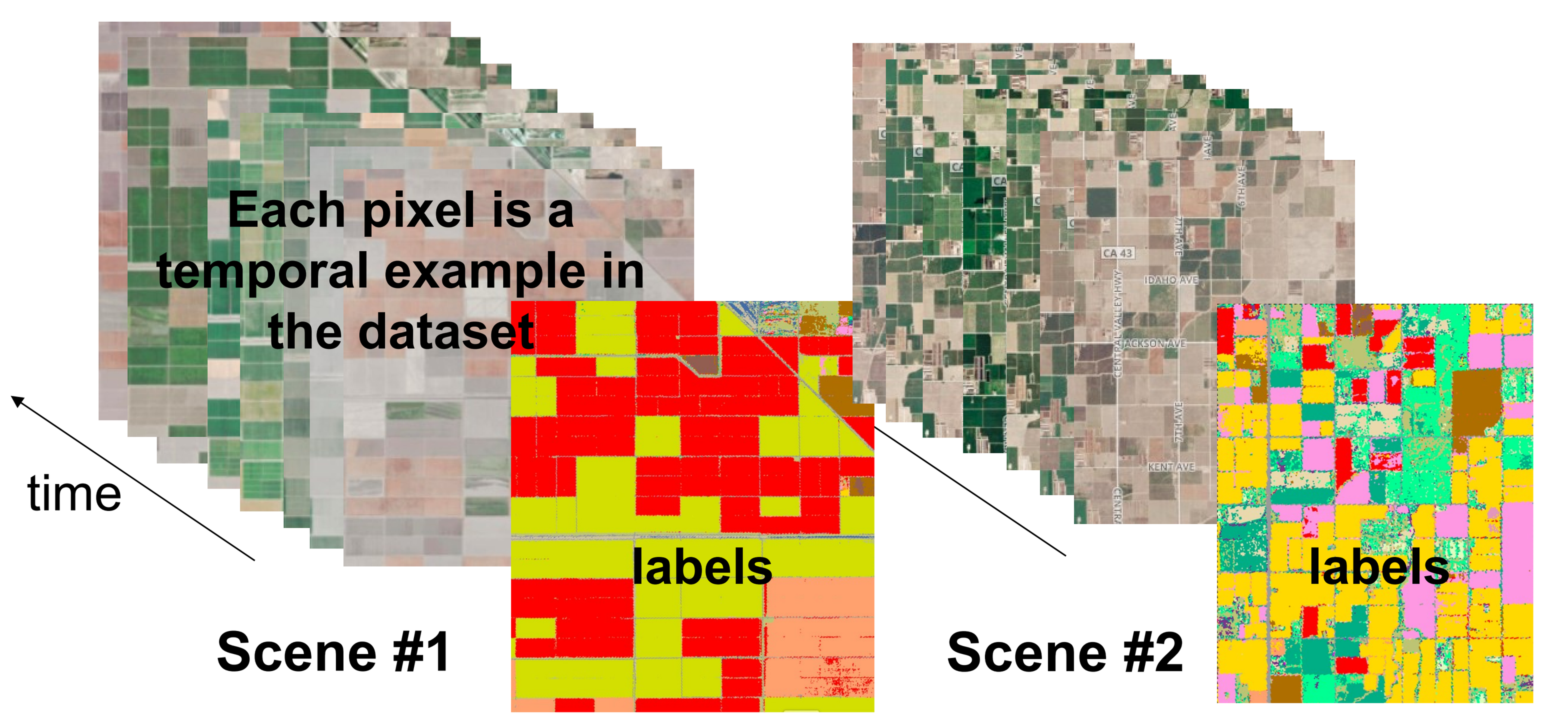
## Overview

I explore the use of time series satellite imagery and supervised machine learning techniques for crop classification. Crop classification is important for understanding the agricultural cover of our evermore populated planet. Studies via satellite imagery are often publicly limited to data with low revisit rates or coarse spatial resolution. A recent surge in "new aerospace" companies such as Planet Labs provide higher cadence data at finer spatial resolution. I explore this temporal pixel information throughout a growing season for crop classification.

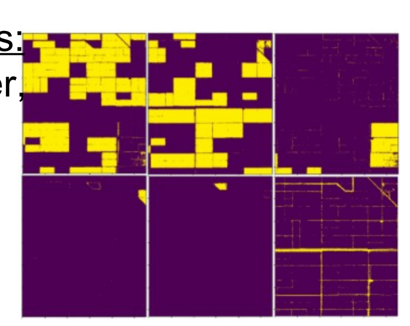
## Dataset Construction

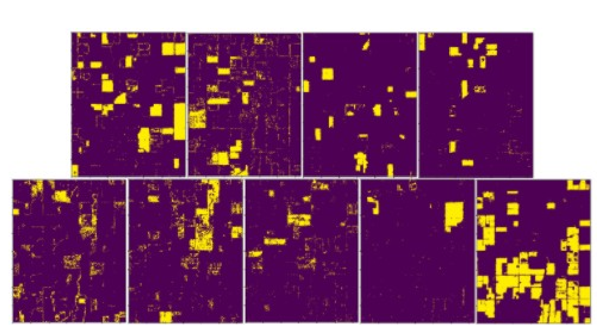
Rapid Eye satellite imagery was gathered from Planet Explorer [1]. Labels were constructed from the USDA Crop Data Layer (CDL) [2] and were sampled to match the satellite's ground resolution (5 m).
**Per Image:** 5 bands (B, G, R, Red Edge, NIR)
**Per Pixel:** 15 time stamps from February – December 2016




The top crops in each scene (six in **Scene #1** and nine in **Scene #2**) are masked and 100,000 random samples of each crop are added to each associated dataset.

Scene #1 Crops: cotton, safflower, tomatoes, winter wheat, durum wheat, idle land





Scene #2 Crops: alfalfa, almonds, corn, cotton, idle land, pistachios, walnuts, winter wheat, corn/winter wheat

Each pixel location is a data example with a temporal signature across the spectral bands (15x5=75 features). The datasets are split with a 90-05-05 train-validation-test split. Scene #1's dataset has a total of 600,000 data points, while Scene #2's dataset has a total of 900,000 data points.

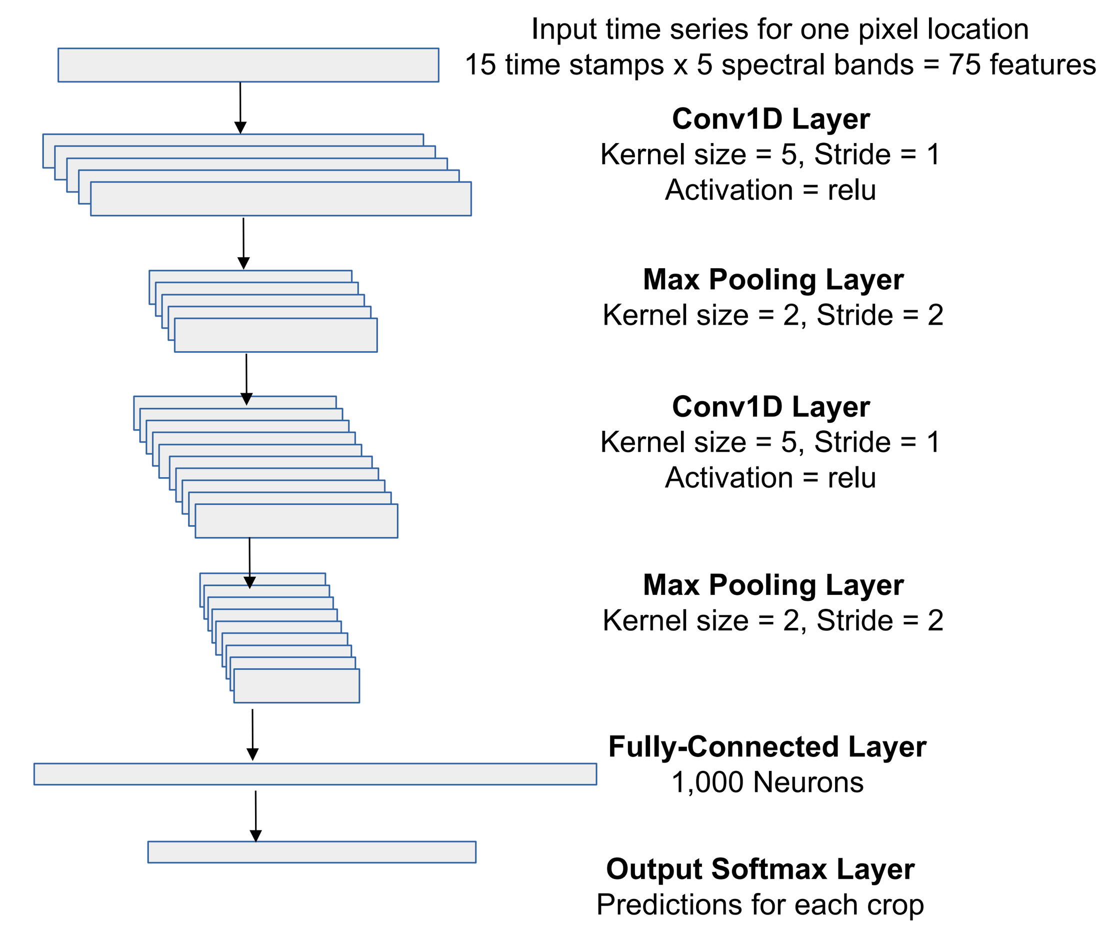
## Methods

Multi-class logistic regression
→ with L2 regularization

Support Vector Machines
→ with RBF kernel
→ reduced training set to 60,000

Simple Neural Network
→ one hidden layer, 200 units
→ relu activation function
→ rross-entropy loss
→ used regularization & dropout
→ Adadelta optimizer

### Convolutional Neural Network




## Thoughts & Future Work

A comparison of mono- vs. multi-temporal results shows that temporal information can be helpful for successful crop classification. I would like to continue this work using Planet data from 2017 for a similar analysis once the USDA Crop Data Layer is released for the 2017 year. The current cadence of Planet satellites is near daily, providing even richer temporal information compared to what was used in this project with 2016 data (~1 image/month).

This analysis shows pixel-by-pixel classification. Incorporation of spatial information into the approach will likely boost performance. Textural features can be incorporated using local binary patterns (LBP) or gray-level co-occurence matrix. To expand into a more complex approach, I would be interested in using entire scenes with temporal information as input.

## Experimental Results

Table 1: Scene 1 Multi-Temporal Results

| | Softmax Reg. | SVMs | Simple NN | CNN |
|---|---|---|---|---|
| Train Accuracy | 92.38 | 96.46 | 92.88 | 95.66 |
| Test Accuracy | 92.06 | 92.21 | 92.06 | 92.64 |

Table 2: Scene 1 Mono-Temporal Results

| | Softmax Reg. | SVMs | Simple NN | CNN |
|---|---|---|---|---|
| Train Accuracy | 81.63 | 86.43 | 86.72 | 87.56 |
| Test Accuracy | 81.56 | 85.79 | 85.96 | 86.01 |

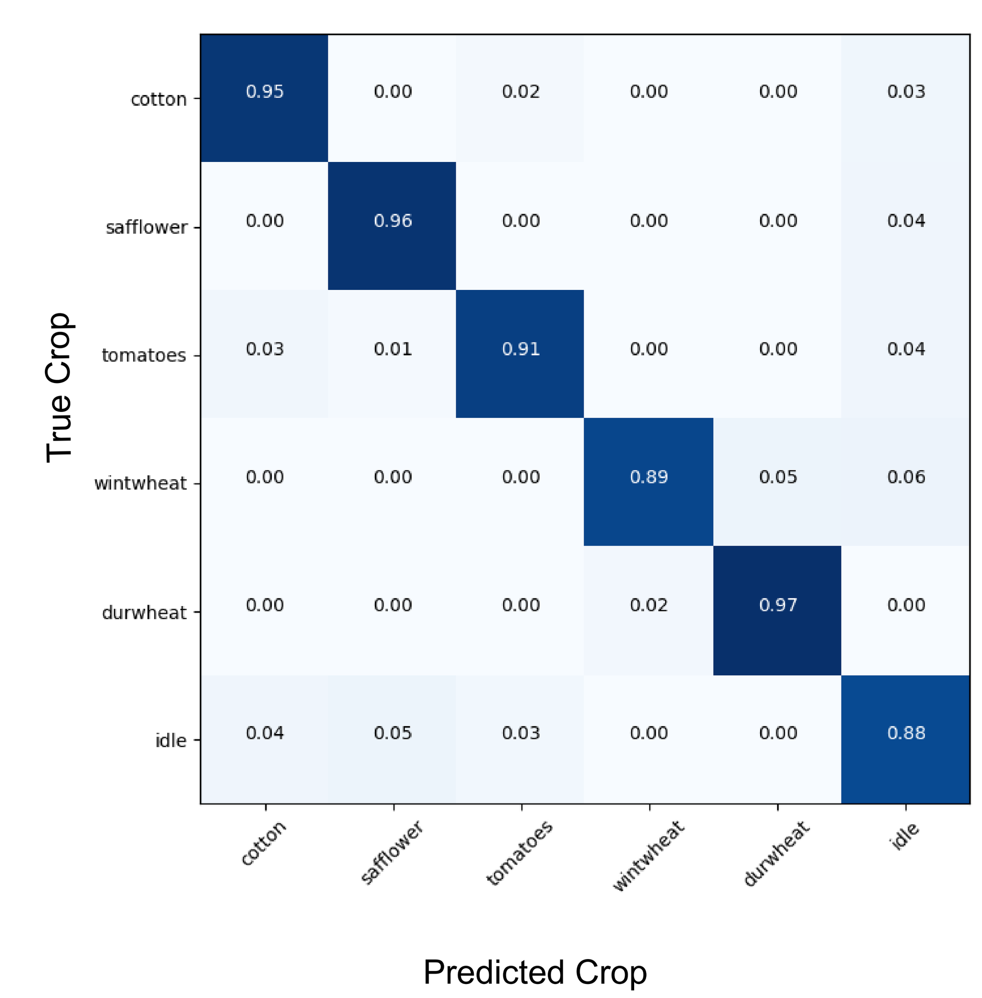
Table 3: Scene 2 Multi-Temporal Results

| | Softmax Reg. | SVMs | Simple NN | CNN |
|---|---|---|---|---|
| Train Accuracy | 76.21 | 85.78 | 81.74 | 87.14 |
| Test Accuracy | 76.05 | 81.07 | 81.43 | 85.50 |

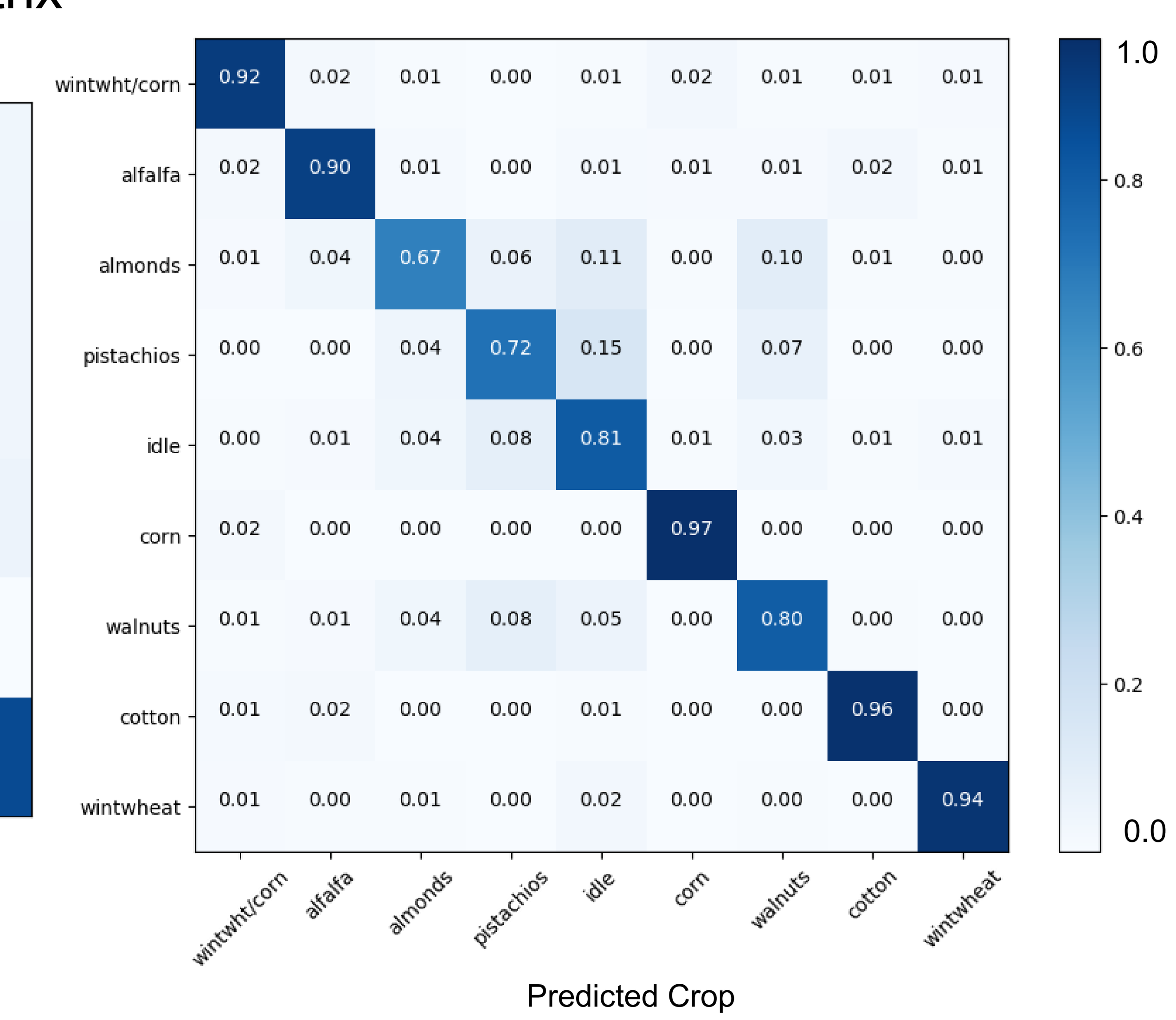
Table 4: Scene 2 Mono-Temporal Results

| | Softmax Reg. | SVMs | Simple NN | CNN |
|---|---|---|---|---|
| Train Accuracy | 47.23 | 53.39 | 48.52 | 57.22 |
| Test Accuracy | 45.26 | 49.93 | 45.87 | 53.65 |

Scene #1 CNN Confusion Matrix




Scene #2 CNN Confusion Matrix




References: [1] https://www.planet.com/products/explorer/ [2] https://nassgeodata.gmu.edu/CropScape/