Sunspot Group Classification using Neural Networks

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Motivation

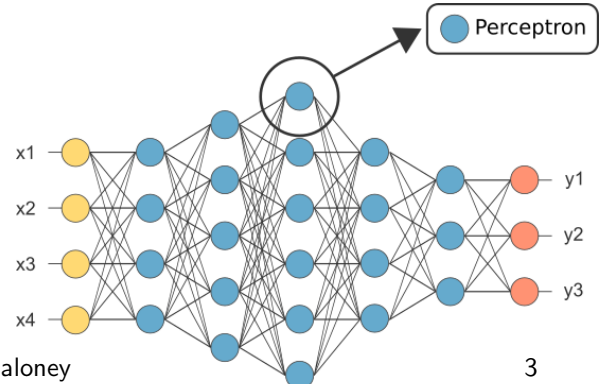
- Use machine learning to:
  - Improve flare forecasts for space weather and observation planning
  - Understand flare triggers (M, C, X or no flare?)
- Sunspot classification as starting point
  - Mt Wilson / Hale 6 classes (Hale et al. 1919)
  - McIntosh 60 classes (McIntosh 1990)
- Classification lifetimes, transition rates, ...
- Classification networks can feed into to larger networks

Neural Networks

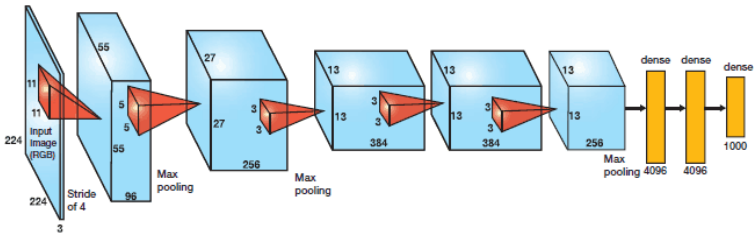
Given y and x learn or infer $f(\quad)$

$$y = f(x)$$

- Model arbitrarily complex functions
- Parameters grow exponentially
- Larger number of parameters requires large data sets
- Spatial information lost



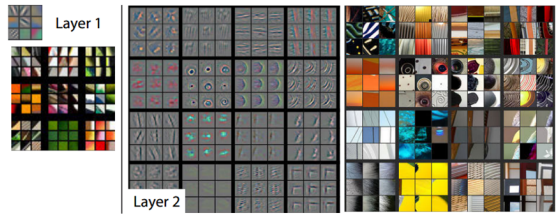
Convolutional Neural Networks



- Reduce model size through parameter sharing
- Spatial information retained
- Most successful architecture for image based tasks

Transfer Learning

- Instead of starting from scratch use a pre-trained model
  - Retrain only the classifier
  - Fine-tune entire network
- Lower network layers detect common features
- Requires less training data



SRS files

- Sunspot Region Summary (SRS)
- U.S. Dept. of Commerce, NOAA, U.S. Air Force
- 1966 - Present (digital)
- Section I Regions with Sunspots

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I. Regions with Sunspots. Locations Valid at 05/2400Z
Nmbr Location  Lo  Area  Z   LL   NN Mag Type
2693 N19W52   332  0010 Axx  01   01 Alpha
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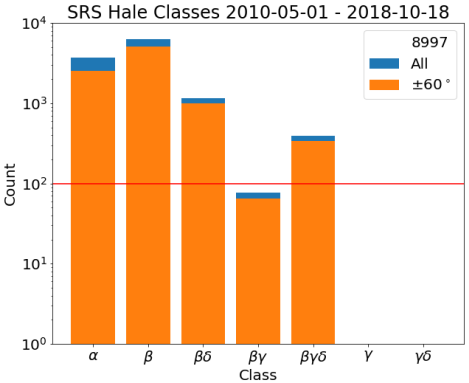
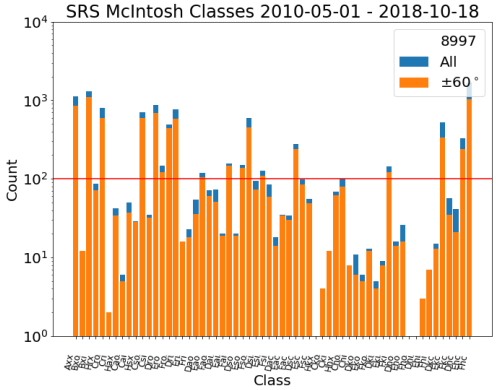
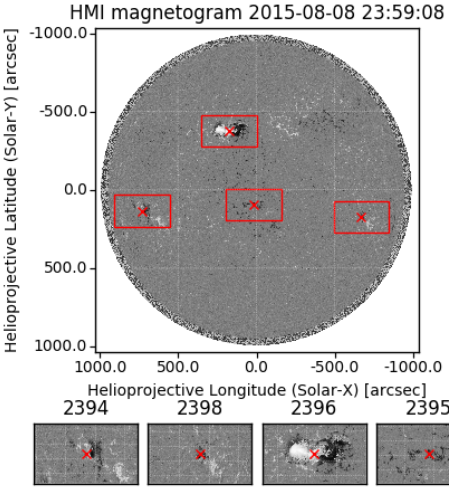
- Reference standard - small number of issues

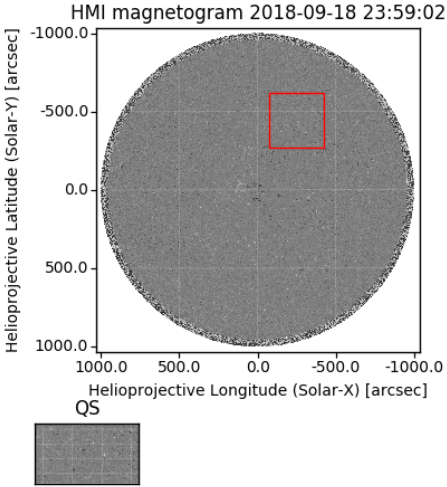
Hale & McIntosh Class Distributions





SDO/HMI


HMI magnetogram 2015-08-08 23:59:08
Helioprojective Latitude (Solar-Y) [arcsec]
Helioprojective Longitude (Solar-X) [arcsec]
-1000.0
-500.0
0.0
500.0
1000.0
2394
2398
2396
2395


HMI magnetogram 2018-09-18 23:59:02
Helioprojective Latitude (Solar-Y) [arcsec]
Helioprojective Longitude (Solar-X) [arcsec]
-1000.0
-500.0
0.0
500.0
1000.0
QS

Classification Metrics

- Accuracy

$$\frac{TP+TN}{P+N}$$

- Precision

$$\frac{TP}{TP+FP}$$

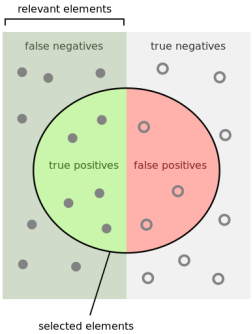
- Recall

$$\frac{TP}{TP+FN}$$

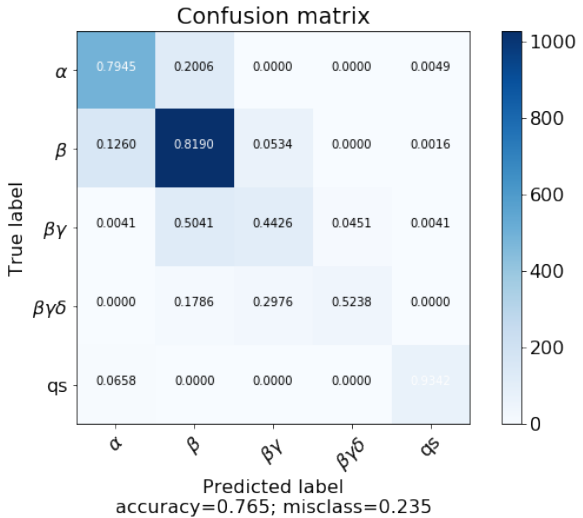
- F_1 Score

$$\frac{precision*recall}{precision+recall}$$

- Confusion Matrix
- ROC curve - TPR vs. FPR as function of threshold



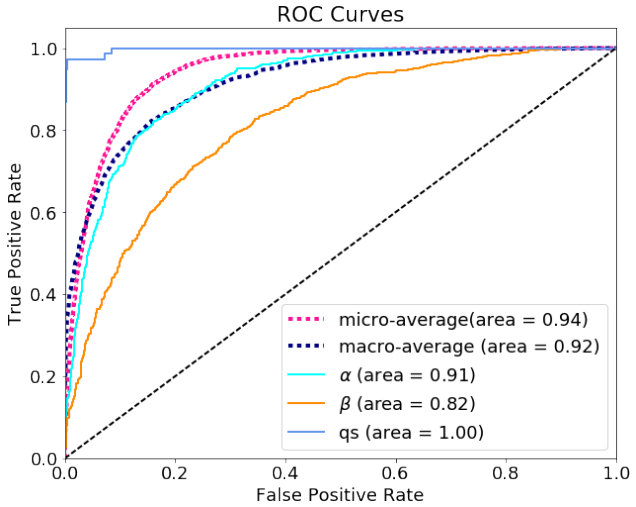
Hale - Confusion Matrix



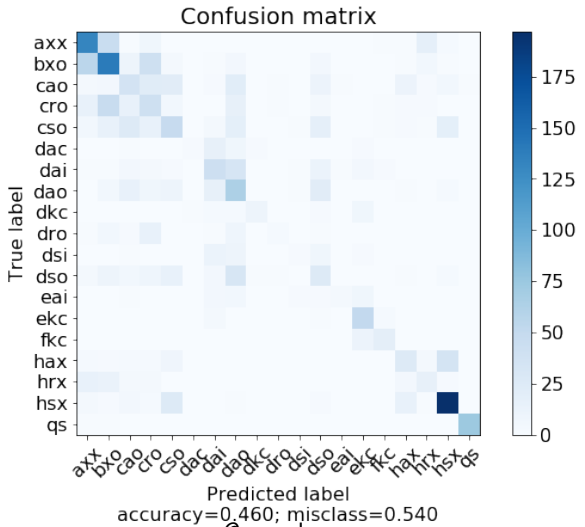
Hale - Precision, Recall and F1 scores

Class	Precision	Recall	F_1-score	Support
α	0.75 (0.80)	0.79 (.79)	0.77 (0.80)	618
β	0.80 (0.48)	0.82 (0.82)	0.81 (0.61)	1254
$\beta\gamma$	0.54 (0.65)	0.44 (0.44)	0.49 (0.49)	244
$\beta\gamma\delta$	0.80 (0.92)	0.52 (0.52)	0.63 (0.67)	84
qs	0.92 (0.99)	0.93 (0.93)	0.93 (0.93)	76
micro avg	0.76 (0.70)	0.76 (0.70)	0.77 (0.70)	2276
macro avg	0.76 (0.75)	0.70 (0.70)	0.73 (0.71)	2276
weighted avg	0.76 (0.75)	0.76 (0.70)	0.76 (0.71)	2276

Hale - ROC curves



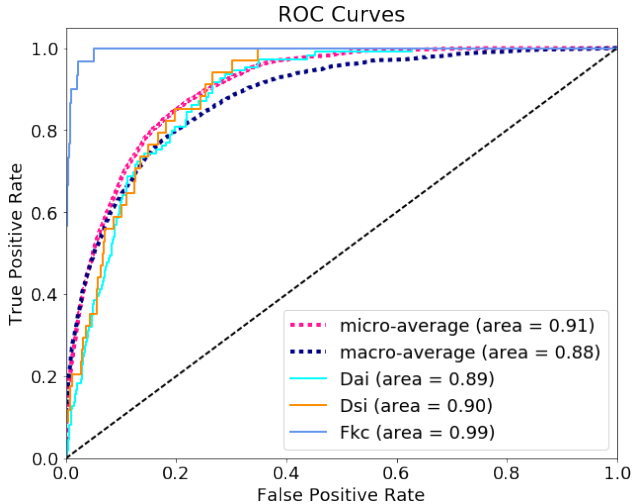
McIntosh - Confusion Matrix



McIntosh - Precision, Recall and F1 scores

Class	Precision	Recall	F_1-score	Support
axx	0.55 (0.46)	0.63 (0.63)	0.59 (0.53)	208
bxo	0.48 (0.30)	0.52 (0.52)	0.50 (0.38)	270
cao	0.28 (0.24)	0.25 (0.25)	0.26 (0.24)	146
cro	0.24 (0.20)	0.28 (0.28)	0.26 (0.23)	148
cso	0.34 (0.31)	0.28 (0.28)	0.31 (0.29)	172
dac	0.67 (0.63)	0.07 (0.07)	0.12 (0.12)	30
dai	0.38 (0.21)	0.39 (0.39)	0.38 (0.27)	109
dao	0.29 (0.17)	0.44 (0.44)	0.35 (0.25)	145
dkc	0.77 (0.84)	0.38 (0.38)	0.51 (0.53)	26
dro	0.50 (0.79)	0.08 (0.08)	0.14 (0.15)	37
dsi	0.29 (0.38)	0.06 (0.06)	0.10 (0.10)	34
dso	0.23 (0.21)	0.23 (0.23)	0.23 (0.22)	112
⋮	⋮	⋮	⋮	⋮
qs	0.99 (0.99)	0.97 (0.97)	0.98 (0.98)	76
micro avg	0.44 (0.40)	0.44 (0.40)	0.44 (0.40)	2026
macro avg	0.44 (0.51)	0.38 (0.40)	0.39 (0.38)	2026
weighted avg	0.43 (0.51)	0.44 (0.40)	0.42 (0.38)	2026

McIntosh- ROC curves



Conclusions

- Hale classification accuracy on 5 classes 76% (70%) [no skill 20%]
- McIntosh classification accuracy on 19 classes 46% (39%) [no skill 5.2%]
- Preliminary results from non-optimised network encouraging
- Class imbalance e.g. Bxo: 1309, Chi: 2, Fri: 0
  - Difficult to overcome for extremely rare classes → create a new class containing all rare classes

Next Steps

Increase Sample Size:

- Additional Classifications
  - UK Met Office (manual, 6 hour cadence)
  - Korean Space Weather Center, ASSA (automated, hourly)
- Include observations $\sim \pm 30$ minutes of SRS classification
- SOHO/MDI + SDO/HMI 1996 - present two cyles

Neural Network Techniques:

- Optimise network hyper parameters
- Only train the last n layers of network
- Data augmentation
- Generate adversarial examples
- Regularisation