Estimating Physical Stellar Parameters from High Resolution Spectra with a Deep Learning Regression Approach

Supervisor

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Master's Thesis by

Jakob Salomonsson

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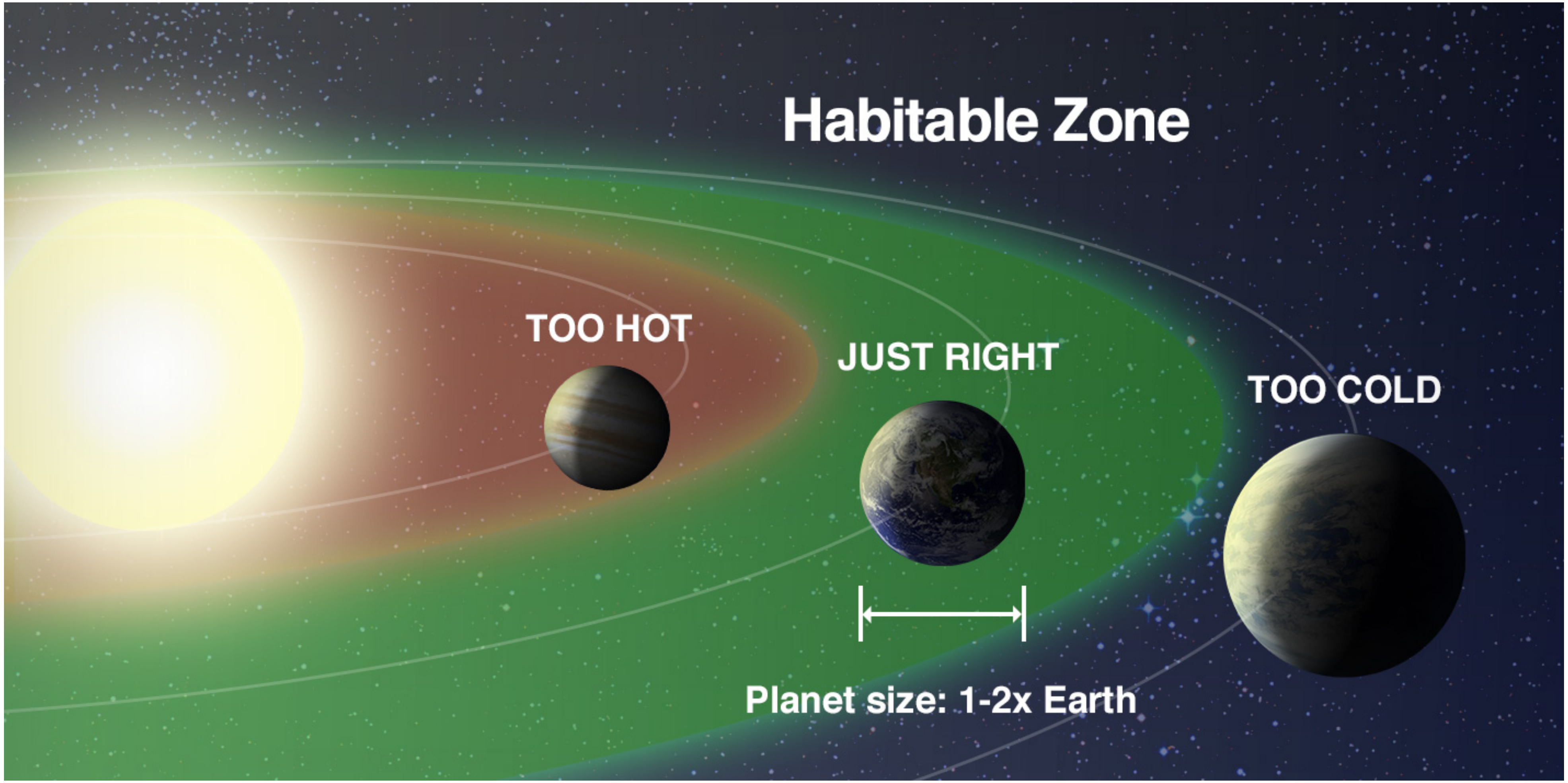
Technical University of Madrid (UPM)

Objective of this Master’s Thesis

To evaluate the capabilities of Deep Learning, with a Regression approach, on estimating physical stellar parameters from spectra.

Why estimating physical stellar parameters?



Source: NASA

What are the "Physical Stellar Parameters"?

- Effective temperature:

  - At what distance can the planets be considered to be within the habitable zone.

- Surface gravity

  - Can the planet retain an atmosphere?
  - Geologically alive?

- Metallicity

  - All elements that are heavier than hydrogen or helium.
  - A high metallicity is probably needed to retain habitable planets.

Spectra (Matrix) Creation

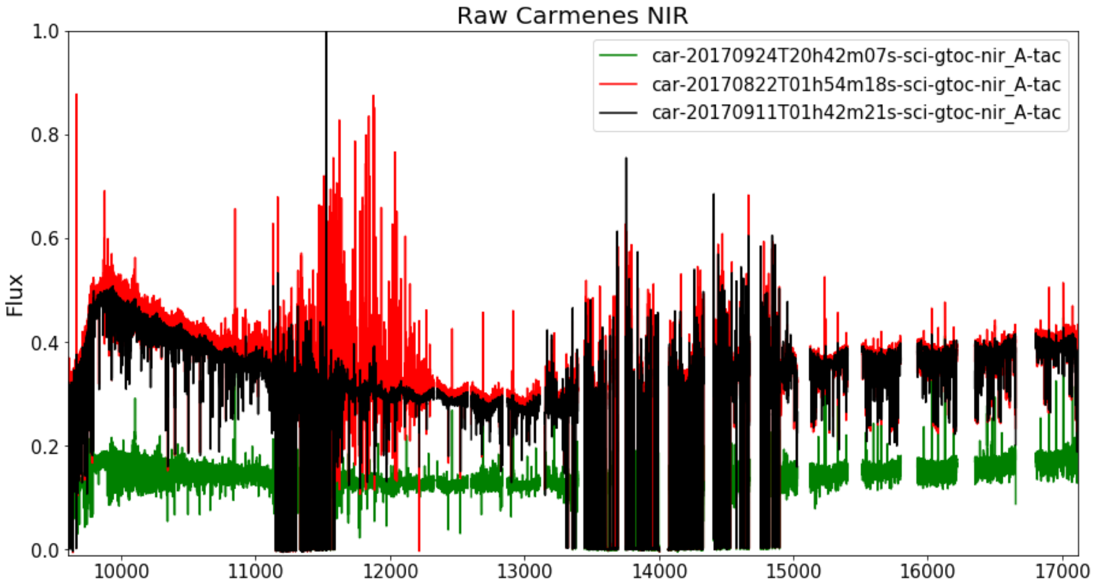
BT-Settl (SVO)

- Theoretical data set
- Low resolution
- 62 GB

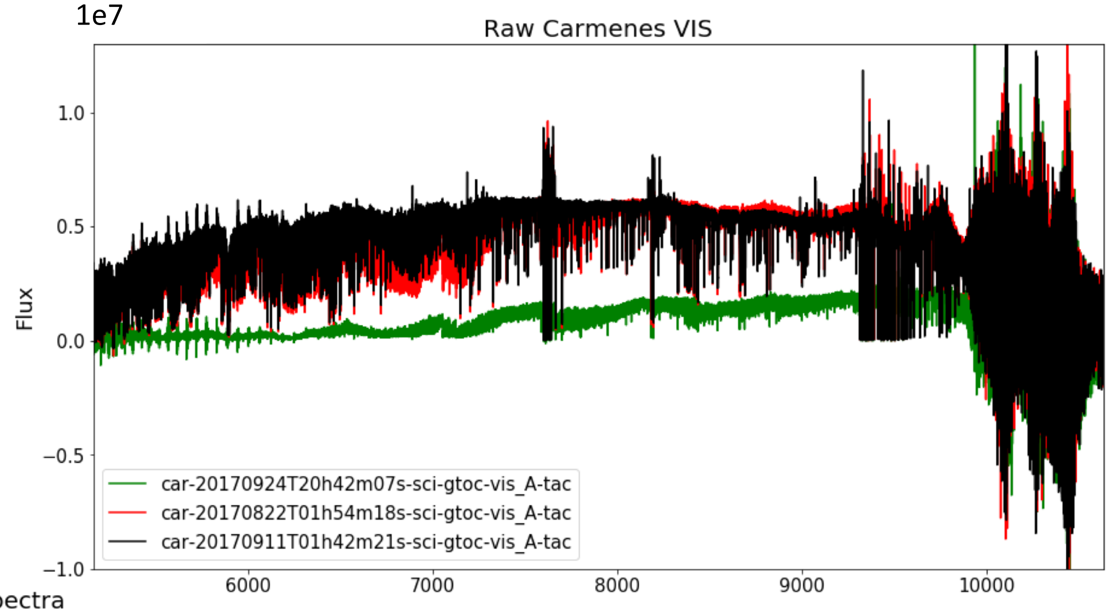
Carmenes (CARMENES consortium)

- Observed data set
- High resolution
- 100 MB

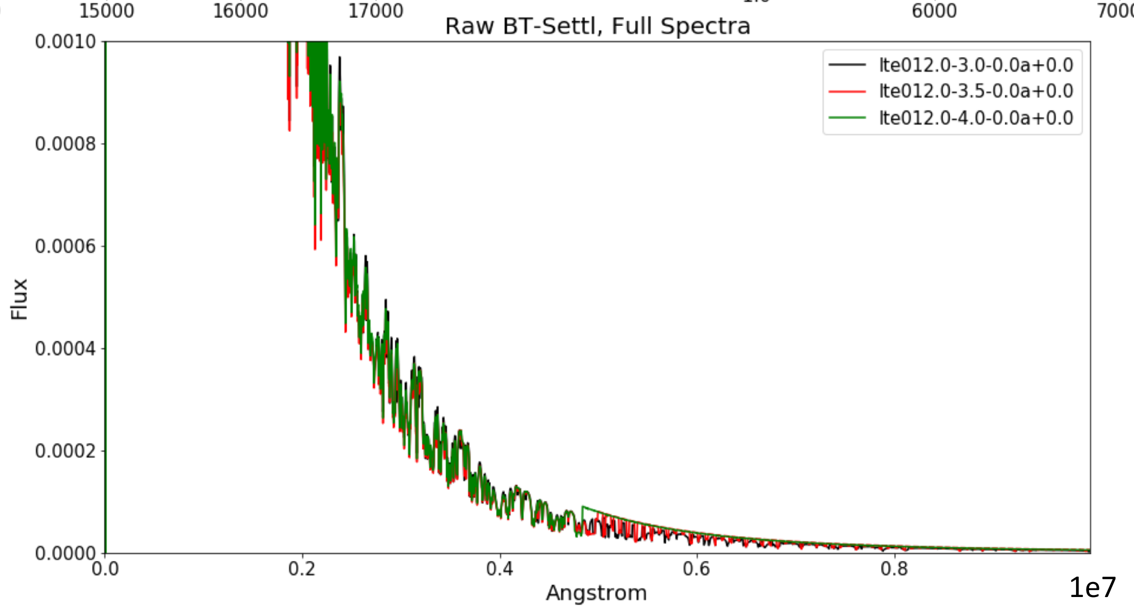
Raw Carmenes and BT-Settl data sets



114,000 data points/file



250,000 data points/file



350,000 - 1,200,000 data points/file

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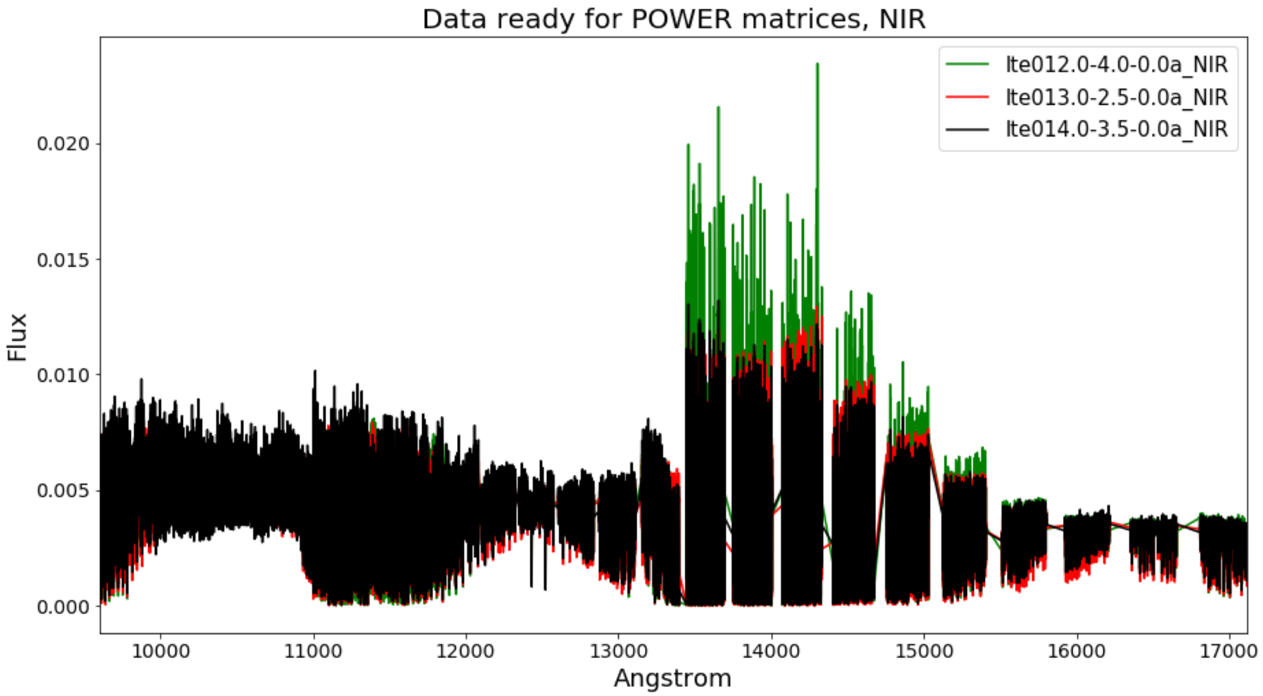
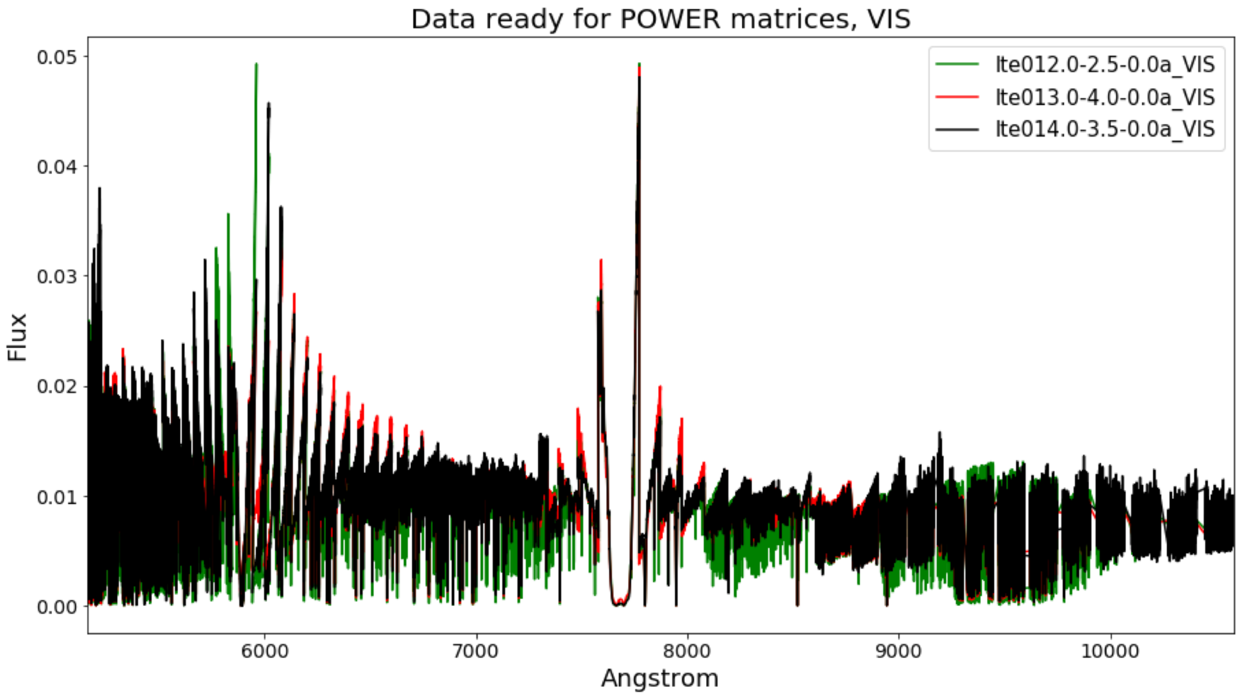
Pre-processed Data





From 16h to 75s per file.
An improvement of around 750 times!

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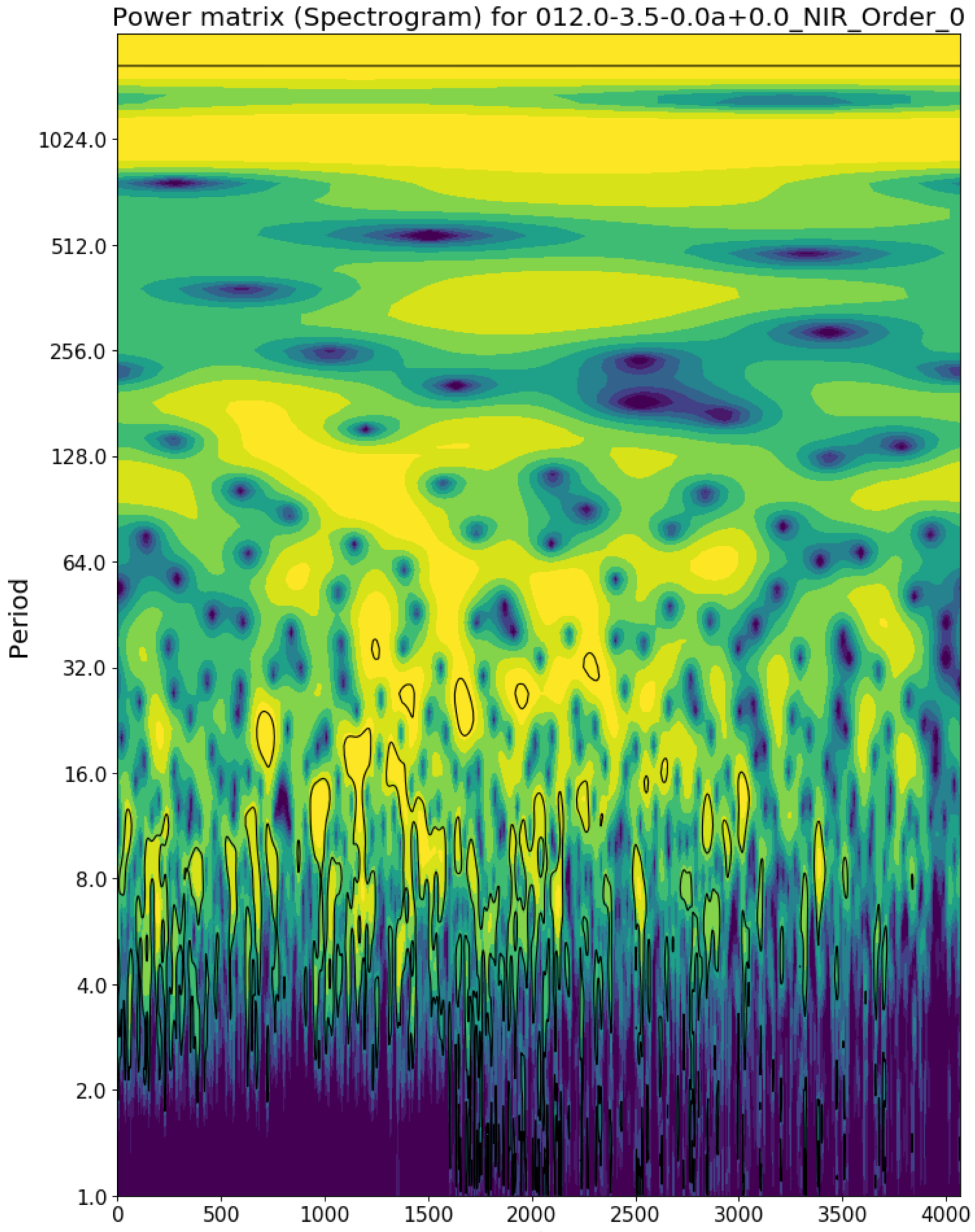
The resulting Spectra

	VIS	NIR
Matrices created	1020	1024
Size	7747 x 2871	3724 x 4073
Number of Orders	61	28
Total size on disk (GB)	55	38



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Main Models

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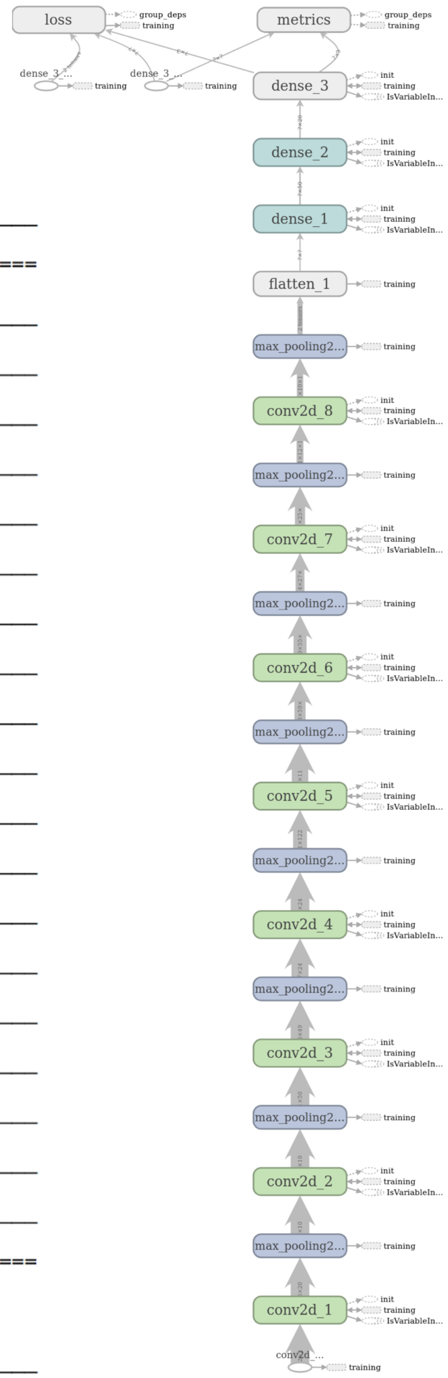
Main CNN Architecture

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 1856, 2030, 16)	2368
max_pooling2d_1 (MaxPooling2	(None, 928, 1015, 16)	0
conv2d_2 (Conv2D)	(None, 922, 1009, 32)	25120
max_pooling2d_2 (MaxPooling2	(None, 461, 504, 32)	0
conv2d_3 (Conv2D)	(None, 455, 498, 64)	100416
max_pooling2d_3 (MaxPooling2	(None, 227, 249, 64)	0
conv2d_4 (Conv2D)	(None, 223, 245, 128)	204928
max_pooling2d_4 (MaxPooling2	(None, 111, 122, 128)	0
conv2d_5 (Conv2D)	(None, 107, 118, 256)	819456
max_pooling2d_5 (MaxPooling2	(None, 53, 59, 256)	0
conv2d_6 (Conv2D)	(None, 49, 55, 512)	3277312
max_pooling2d_6 (MaxPooling2	(None, 24, 27, 512)	0
conv2d_7 (Conv2D)	(None, 22, 25, 1024)	4719616
max_pooling2d_7 (MaxPooling2	(None, 11, 12, 1024)	0
conv2d_8 (Conv2D)	(None, 9, 10, 1024)	9438208
max_pooling2d_8 (MaxPooling2	(None, 4, 5, 1024)	0
flatten_1 (Flatten)	(None, 20480)	0
dense_1 (Dense)	(None, 50)	1024050
dense_2 (Dense)	(None, 20)	1020
dense_3 (Dense)	(None, 3)	63

Total params: 19,612,557
Trainable params: 19,612,557
Non-trainable params: 0



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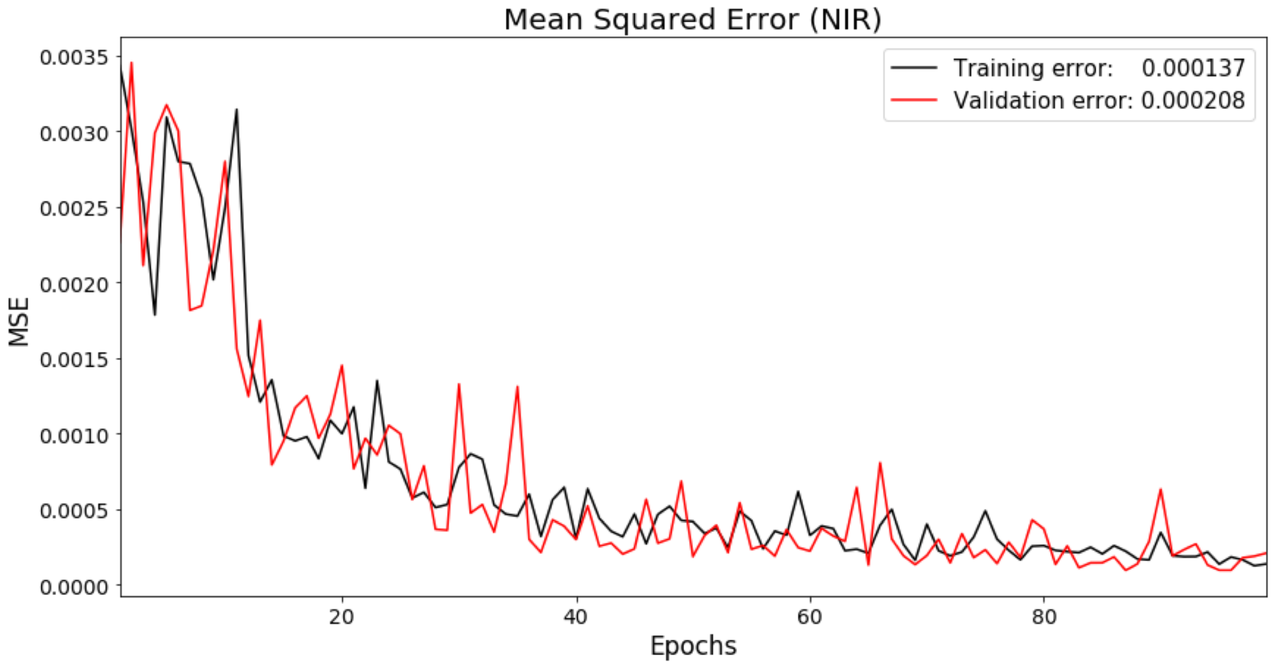
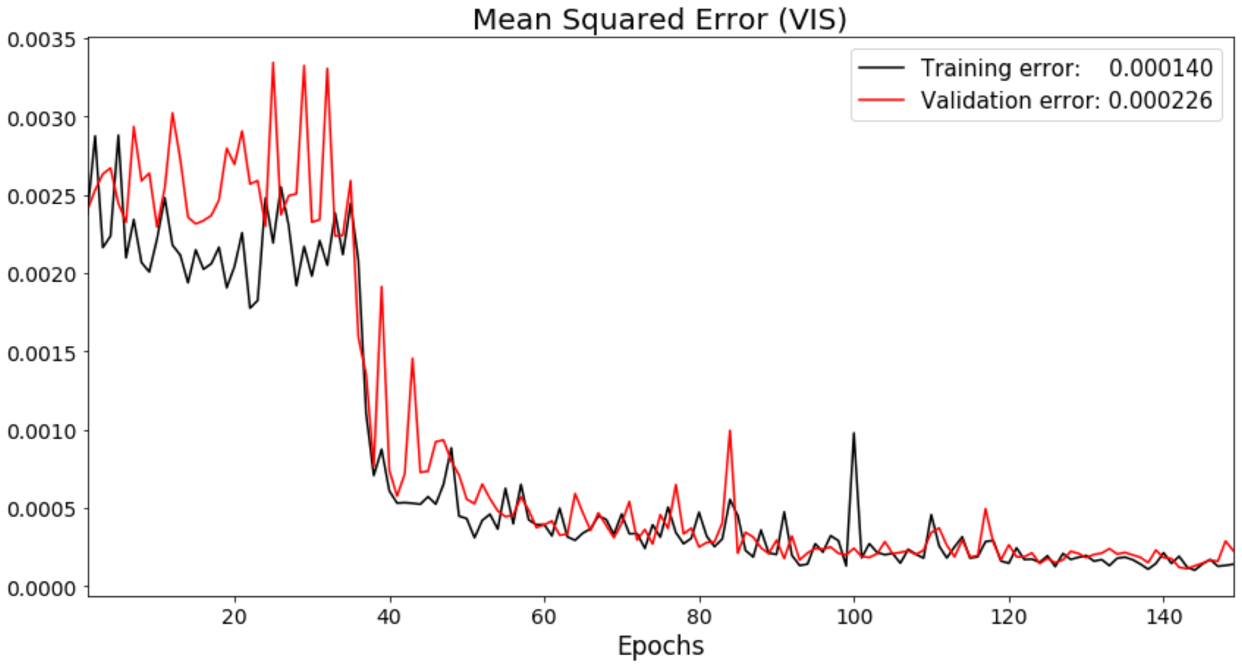
Validation



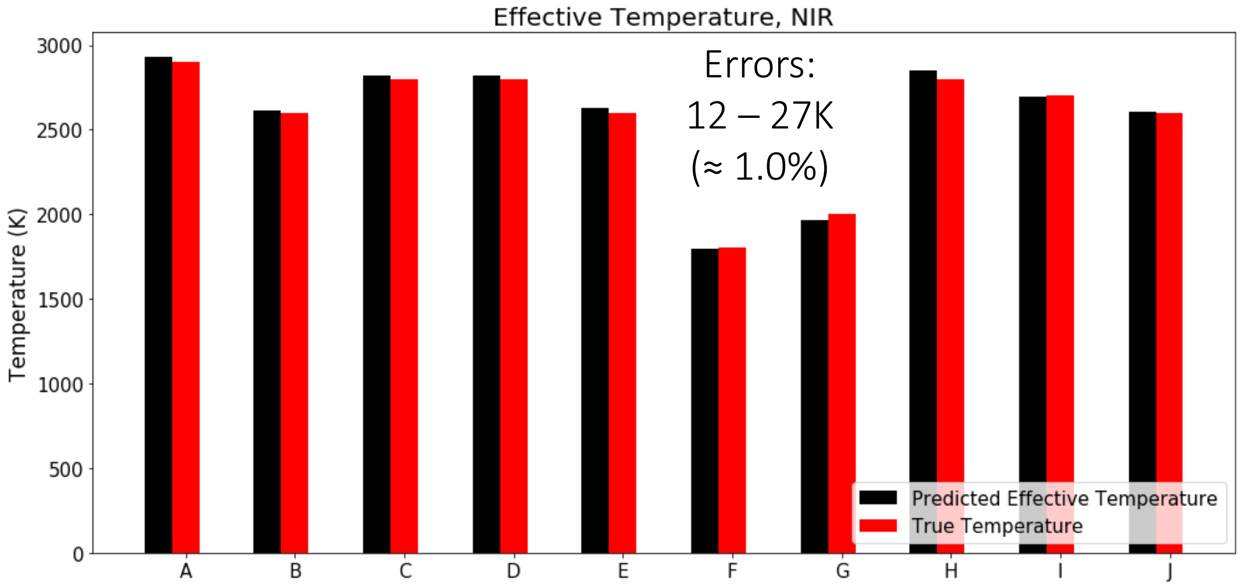
Trained for 18 hours

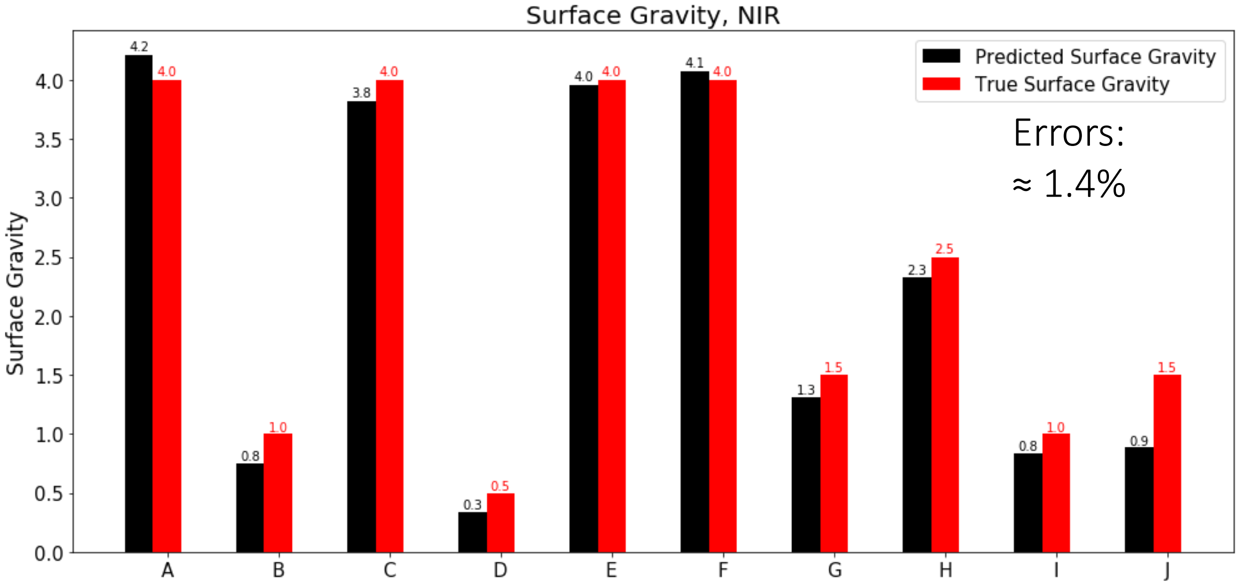


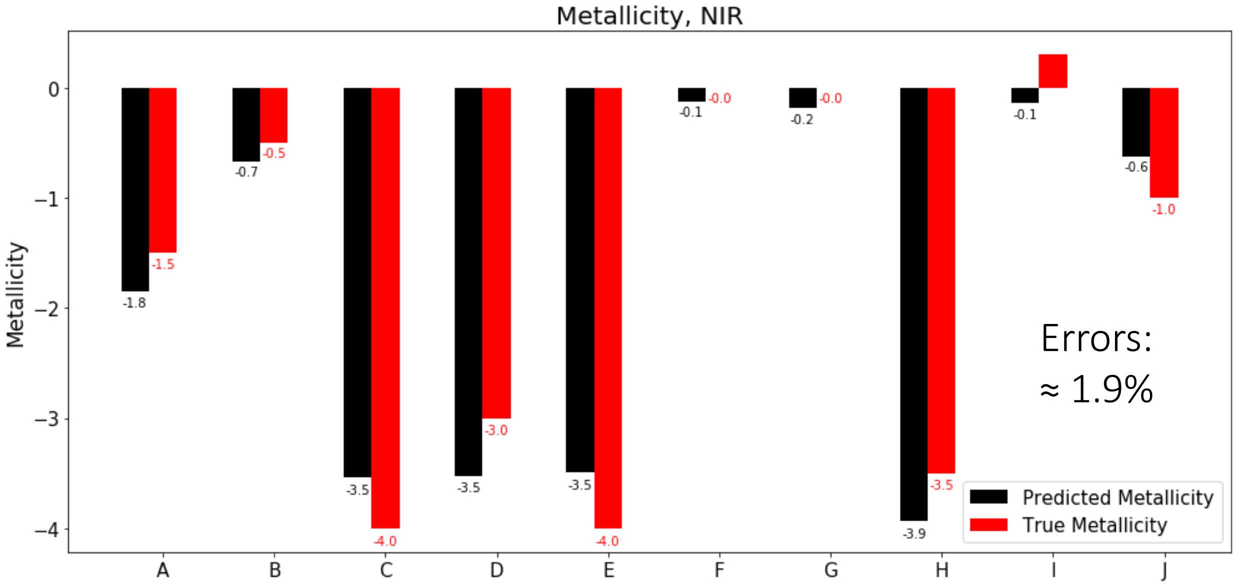
Trained for 37 hours

Estimating Effective Temperature, Surface Gravity and Metallicity on NIR

Performance, NIR model	
Total MSE	0.000103
MSE Effective Temperature	0.000079
MSE Surface Gravity	0.000005
MSE Metallicity	0.003318
Median Sq. Error Eff. Temp.	0.000080
Median Sq. Error Surf. Gravity	0.000196
Median Sq. Error Metallicity	0.000359



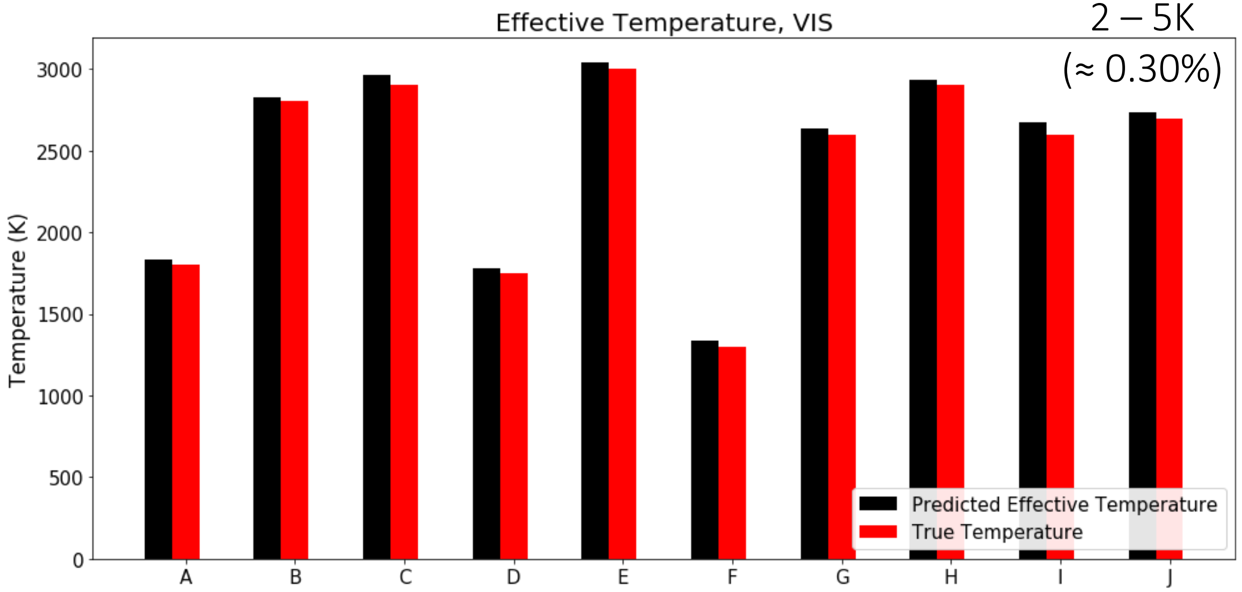


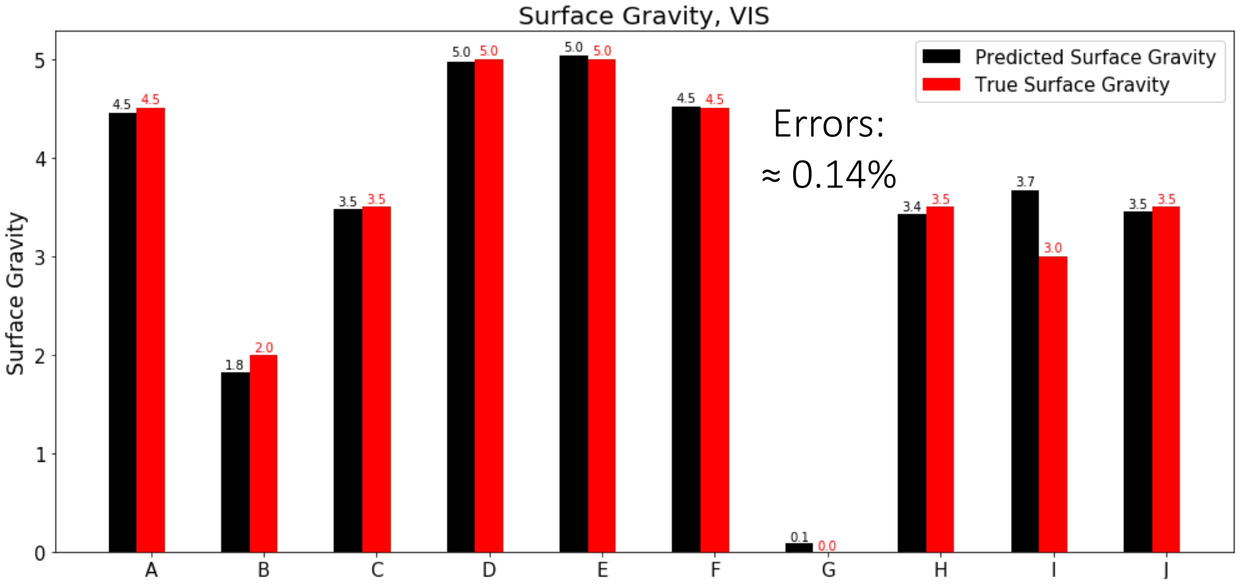


Estimating Effective Temperature, Surface Gravity and Metallicity on VIS

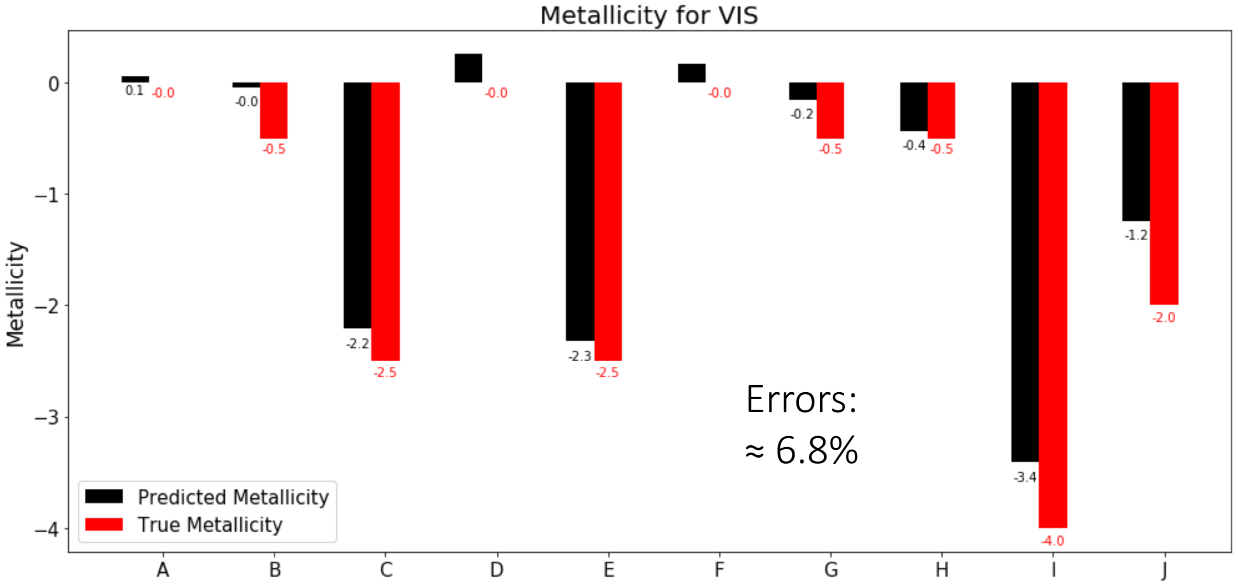
Performance, VIS model	
Total MSE	0.000136
MSE Effective Temperature	0.000003
MSE Surface Gravity	0.018612
MSE Metallicity	0.091275
Median Sq. Error Eff. Temp.	0.000008
Median Sq. Error Surf. Gravity	0.000002
Median Sq. Error Metallicity	0.004638

Errors:
2 – 5K
(≈ 0.30%)





Errors:
≈ 0.14%



Errors:
≈ 6.8%

Down-sized Models
(NIR)

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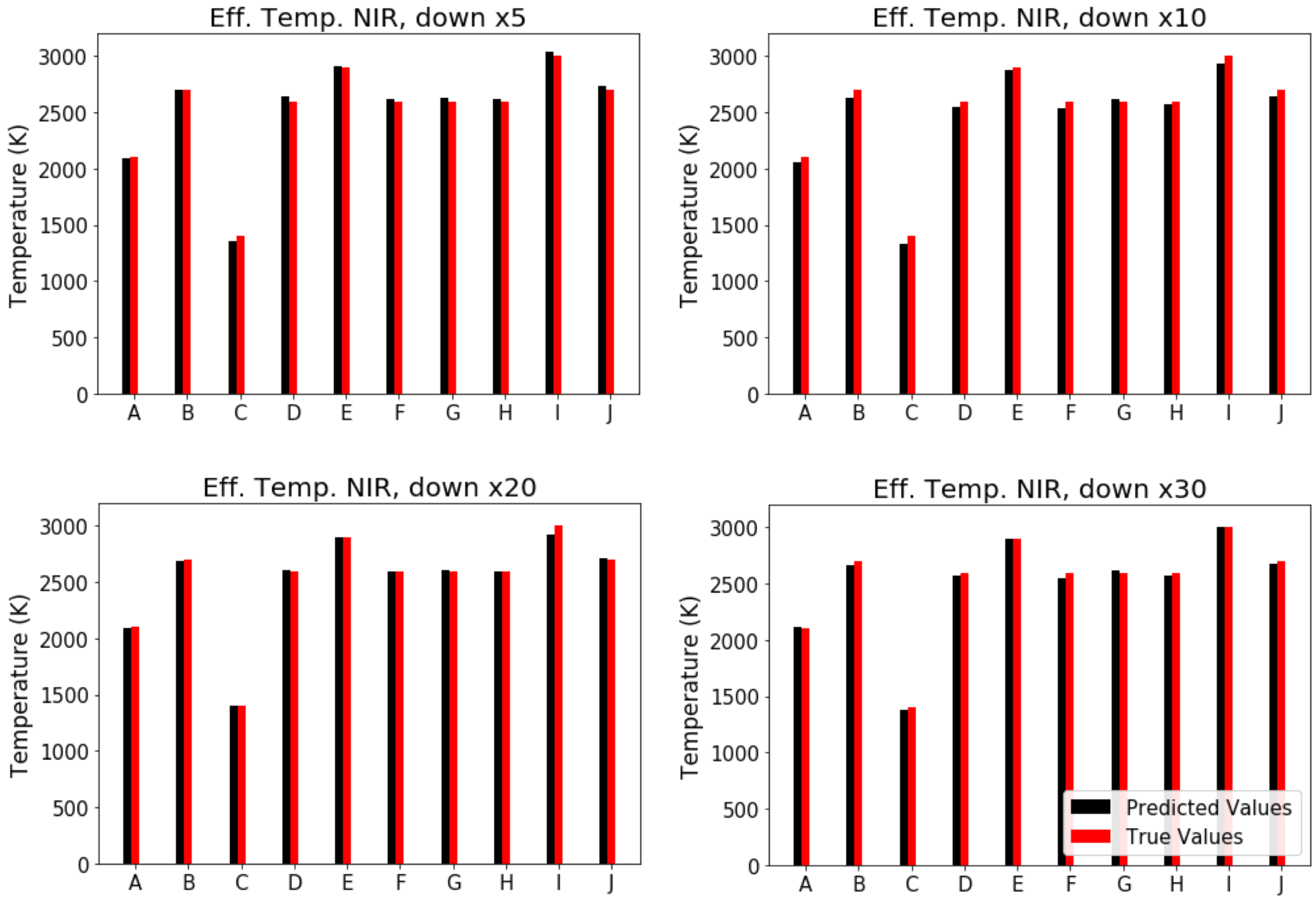
Estimating Effective Temperature with the down-sized input data

The down-sized models are in par with the main models' estimations. However x20 outputs a median error that is substantial lower than the main's.



Estimating Surface Gravity with the down-sized input data

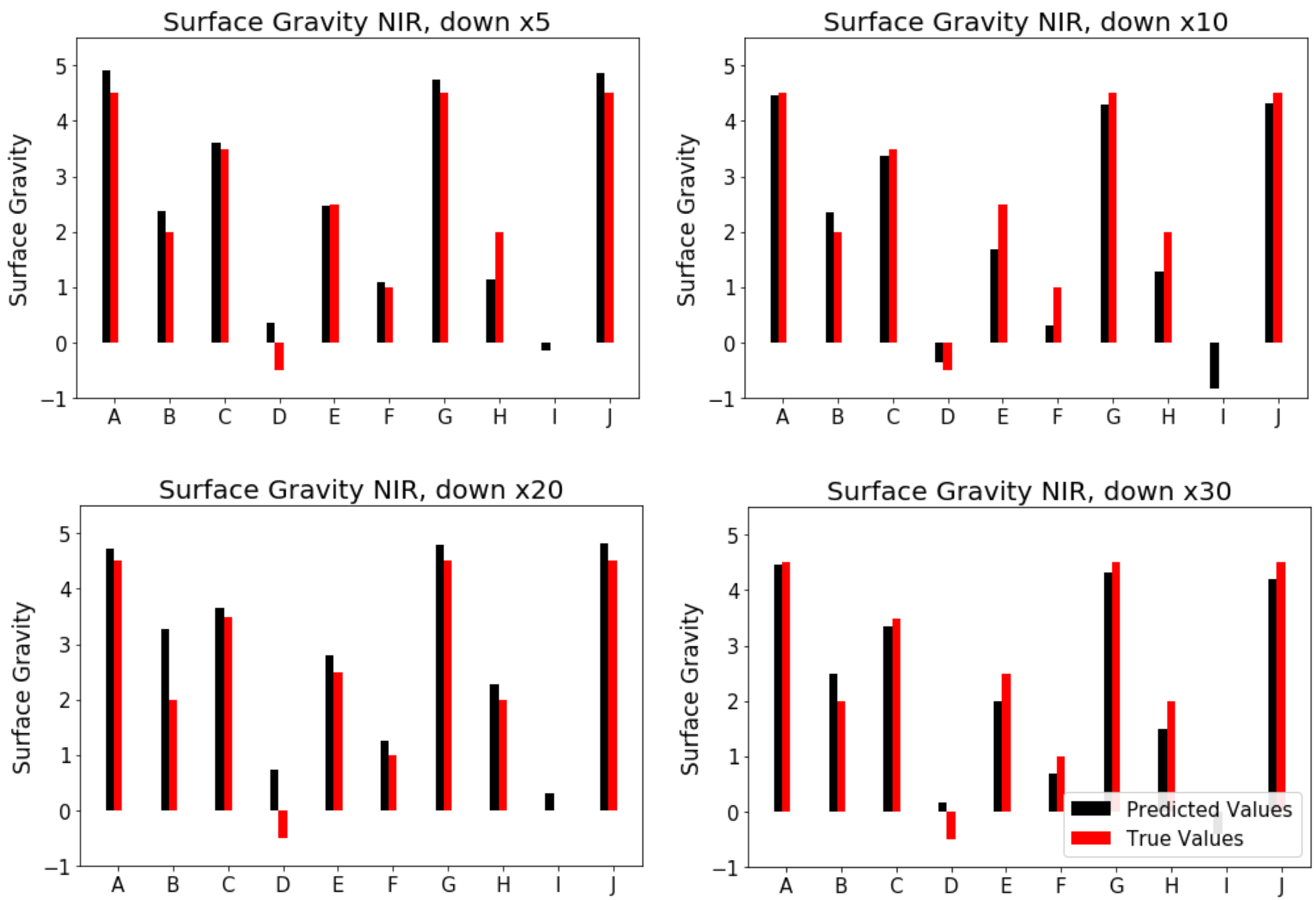
Main model's:

Median Sq. Er.: 0.000196

Best down-sized (x5):

Median Sq. Er.: 0.00246

x13 difference



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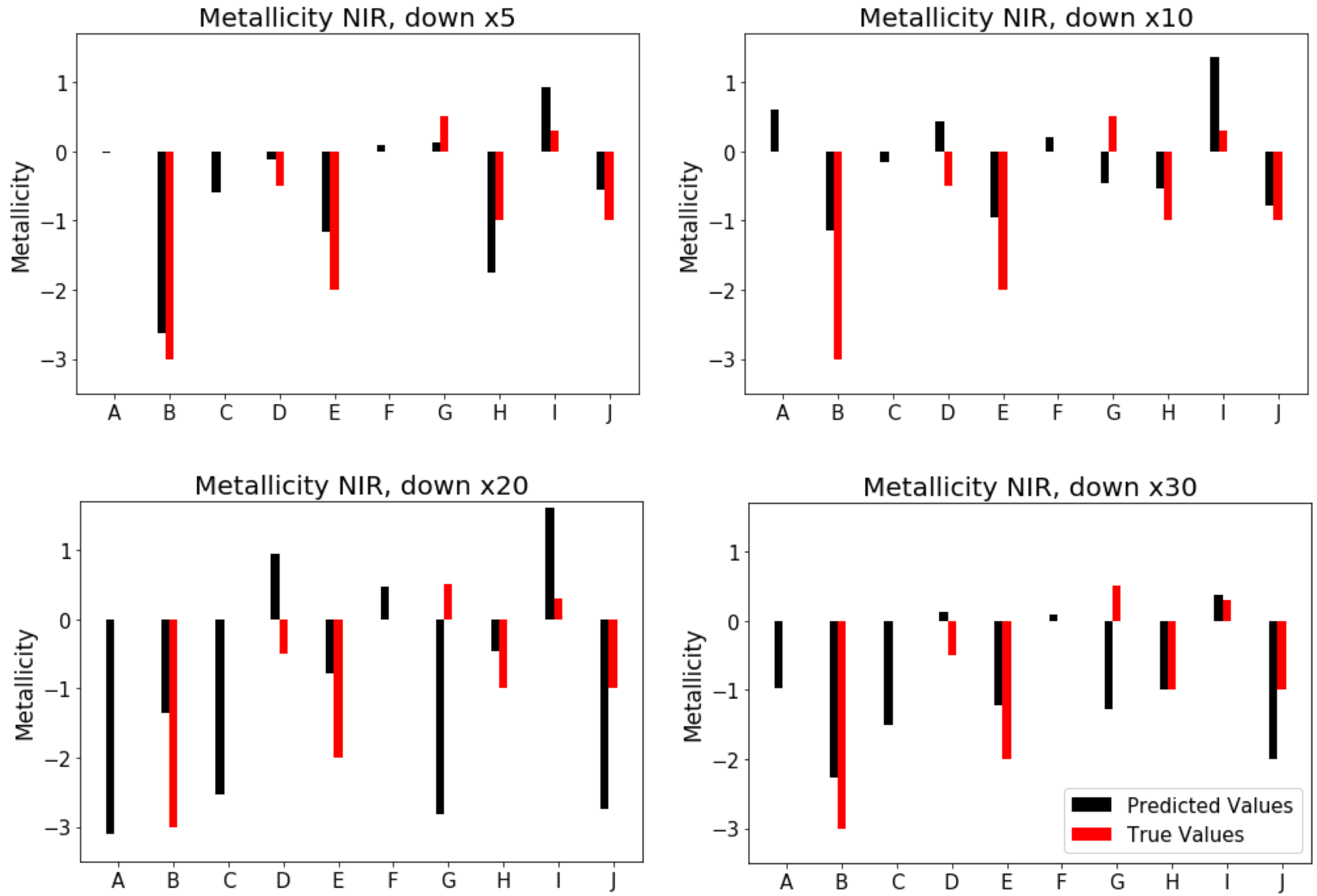
Estimating <u>Metallicity</u> with the down-sized input data

Main model some 35 times better than the best performing down-sized x5 model



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Prediction summary

Model	Training time
x5 NIR	3h 20min
x5 VIS	8h 30min
x10 NIR	3h 40 min
x10 VIS	9h
x20 NIR	3h
x20 VIS	4h 20min
x30 NIR	2h 20min
x30 VIS	4h
main NIR	17h 30min
main VIS	36h 30min

			Median squared	
Model summary	**NIR (MSE)**	**VIS (MSE)**	**NIR**	**VIS**
x5 Effective Temperature	0.000154	0.000237	0.000129	0.000289
x5 Surface Gravity	0.001514	0.184926	0.002462	0.063007
x5 Metallicity	0.002774	0.032663	0.012741	0.000001
x5 Total	0.000389	0.000661	------------	------------
x10 Effective Temperature	0.000123	0.000054	0.000099	0.000064
x10 Surface Gravity	0.002595	0.001861	0.002822	0.004042
x10 Metallicity	0.051235	0.000140	0.213698	0.000043
x10 Total	0.000813	0.000275	------------	------------
x20 Effective Temperature	0.000002	0.000066	0.0000004	0.000039
x20 Surface Gravity	0.037693	0.013175	0.007739	0.000149
x20 Metallicity	0.001388	0.154711	0.101900	0.001923
x20 Total	0.003196	0.000761	------------	------------
x30 Effective Temperature	0.000056	0.000058	0.000073	0.000064
x30 Surface Gravity	0.007950	0.001268	0.009446	0.003123
x30 Metallicity	0.050085	0.001189	0.031612	0.000002
x30 Total	0.001020	0.000319	------------	------------
Main model Eff. Temp	0.000079	0.000003	0.000080	0.000008
Main model Surface Gravity	0.000005	0.018612	0.000196	0.000002
Main model Metallicity	0.003318	0.091275	0.000359	0.004638
Main model Total	0.000103	0.000136	------------	------------

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Estimating Parameters on the Carmenes data

NIR

Matrix name	Eff. Temperature (K)	Surface Gravity	Metallicity
car-20170520T20h38m14s-sci-gtoc-nir	2260	1,9	-1,1
car-20170609T20h33m03s-sci-gtoc-nir	2411	1,7	-1,8
car-20170822T01h54m18s-sci-gtoc-nir	2356	1,8	-1,3
car-20170825T00h06m21s-sci-gtoc-nir	2418	1,7	-1,9
car-20170911T01h42m21s-sci-gtoc-nir	2355	1,8	-1,3
car-20170912T02h41m57s-sci-gtoc-nir	2355	1,8	-1,3
car-20170913T21h52m13s-sci-gtoc-nir	2412	1,6	-1,3
car-20170914T03h24m58s-sci-gtoc-nir	2367	1,7	-1,5
car-20170924T20h42m07s-sci-gtoc-nir	2401	1,7	-1,2

VIS

Matrix name	Eff. Temperature (K)	Surface Gravity	Metallicity
car-20170520T20h38m14s-sci-gtoc-vis	2791	2,0	0,1
car-20170609T20h33m03s-sci-gtoc-vis	2782	1,8	0,3
car-20170822T01h54m18s-sci-gtoc-vis	2845	1,9	-0,3
car-20170825T00h06m21s-sci-gtoc-vis	2796	2,2	0,4
car-20170911T01h42m21s-sci-gtoc-vis	2854	1,9	-0,7
car-20170912T02h41m57s-sci-gtoc-vis	2813	2,2	0,4
car-20170913T21h52m13s-sci-gtoc-vis	2742	2,1	2,6
car-20170914T03h24m58s-sci-gtoc-vis	2783	1,8	1,1
car-20170924T20h42m07s-sci-gtoc-vis	2813	2,1	0,4

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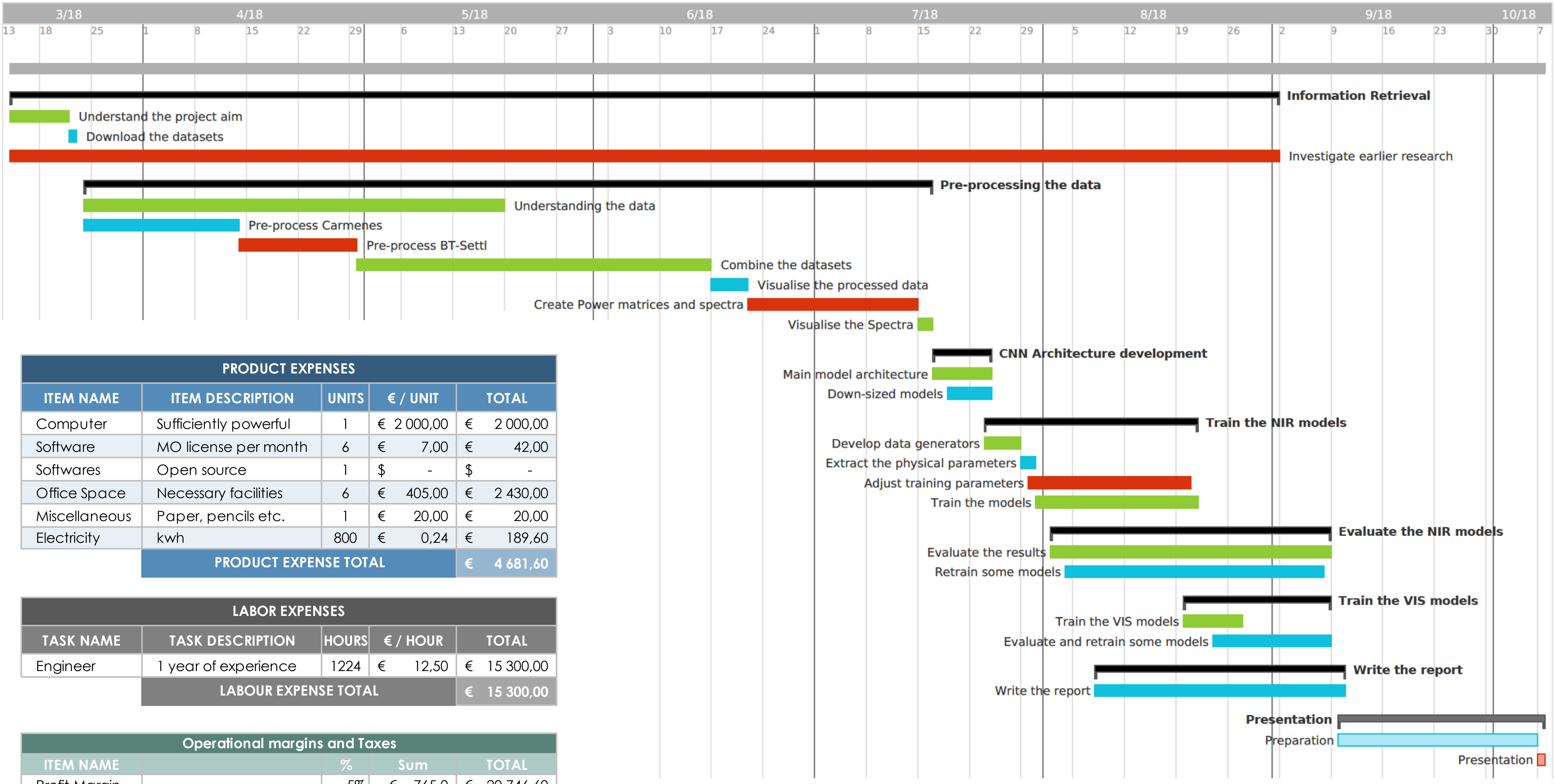
Gantt Chart and Budget



PRODUCT EXPENSES				
ITEM NAME	**ITEM DESCRIPTION**	**UNITS**	**€ / UNIT**	**TOTAL**
Computer	Sufficiently powerful	1	€ 2 000,00	€ 2 000,00
Software	MO license per month	6	€ 7,00	€ 42,00
Softwares	Open source	1	$ -	$ -
Office Space	Necessary facilities	6	€ 405,00	€ 2 430,00
Miscellaneous	Paper, pencils etc.	1	€ 20,00	€ 20,00
Electricity	kwh	800	€ 0,24	€ 189,60
	PRODUCT EXPENSE TOTAL			€ 4 681,60

LABOR EXPENSES				
TASK NAME	**TASK DESCRIPTION**	**HOURS**	**€ / HOUR**	**TOTAL**
Engineer	1 year of experience	1224	€ 12,50	€ 15 300,00
	LABOUR EXPENSE TOTAL			€ 15 300,00

Operational margins and Taxes				
ITEM NAME		**%**	**Sum**	**TOTAL**
Profit Margin		5%	€ 765,0	€ 20 746,60
Cost Margin		9%	€ 1 867,2	€ 22 613,79
VAT		21%	€ 4 748,9	€ 27 362,69
				€ 27 362,69

Conclusions

- A DLR approach estimates the three parameters with high precision.
- Down-sizing works great!
- The **NIR** model seemingly estimates Metallicity with higher precision while the **VIS's** do so for T_{eff} and Surface Gravity.
- Although expected, there are no guarantees that the theoretical and real spectra are sufficient similar for reliable predictions.

Special Thanks to

- Tutor:
  - Joaquin Ordieres Meré
- Other colleagues at the institution:
  - Ebru, Hossein, Isaac, John, José, Sun
- My family:
  - Susanne, Ulf, Maja, Artur, Lydia

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Thank you for your attention

Supervisor

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