

RECOGNITION OF TOTAL ECLIPSES IN BINARIES WITH COMPUTER VISION

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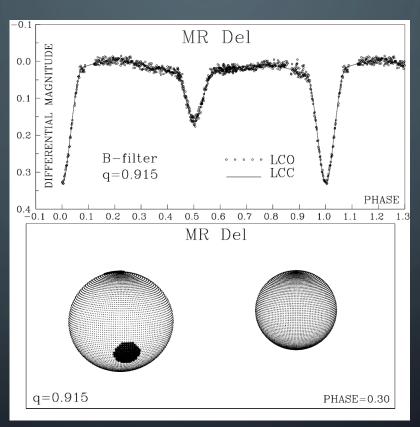
PROGRAM

- Eclipsing binaries
 - Modeling, automation, applications of ML
 - Contact binaries, importance of total eclipses
- Adventures with computer vision
 - Commercial image recognition model (CustomVision)
 - Custom-made image recognition model
 - Application on Kepler and ASAS data

ECLIPSING BINARIES

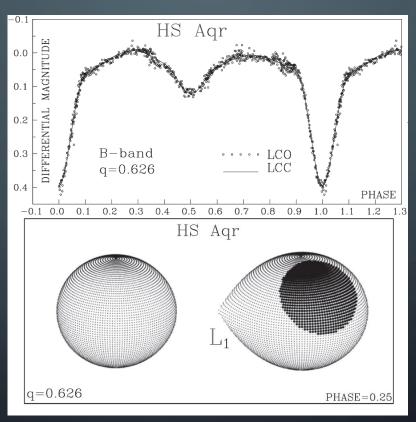
- Binary systems (mostly close) where component stars eclipse each other during each orbit
- At the forefront of astrophysics
- Measurement of stellar masses, radii and temperatures
 from first principles and simple geometric arguments
- Parameters are traditionally determined by modeling

MODELING ECLIPSING BINARIES DETACHED



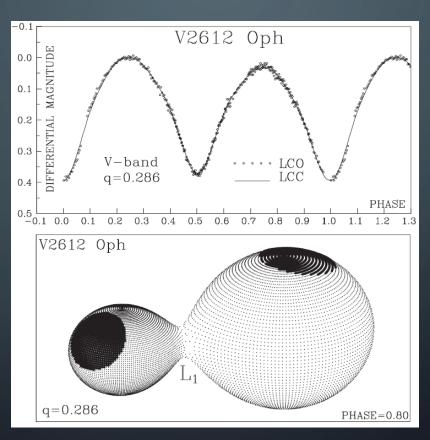
Light curve and model of MR Del From Djurasevic et al., 2011, A&A, 525

MODELING ECLIPSING BINARIES SEMI-DETACHED



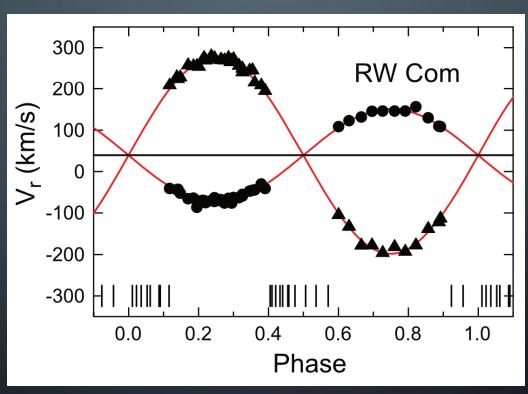
Light curve and model of HS Aqr From Djurasevic et al., 2013, AJ, 145

MODELING ECLIPSING BINARIES CONTACT



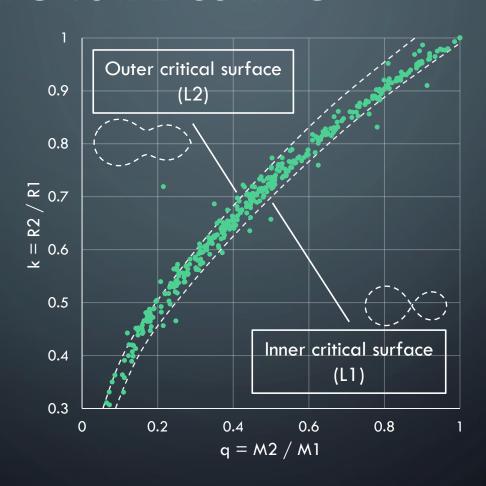
Light curve and model of V2612 Oph From Caliskan et al., 2014, AJ, 148

MODELING ECLIPSING BINARIES MASS RATIO FROM SPECTROSCOPY

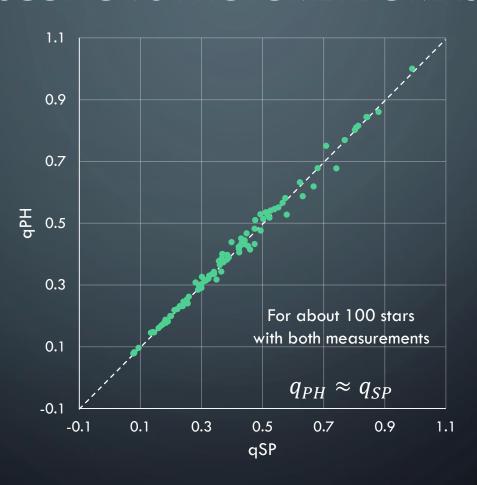


Radial velocity curves of RW Com From Pribulla et al., 2009, AJ, 137

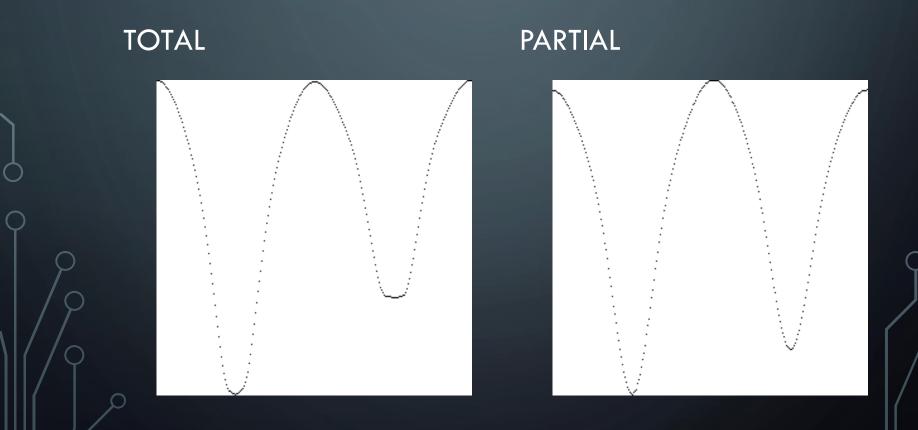
CONTACT BINARIES MASS RATIO VS RADIUS RATIO



CONTACT BINARIES SPECTROSCOPIC VS PHOTOMETRIC MASS RATIO



TOTAL VS PARTIAL ECLIPSES EASY EXAMPLES (FROM KEPLER)



TOTAL VS PARTIAL ECLIPSES HARD EXAMPLES (FROM ASAS)

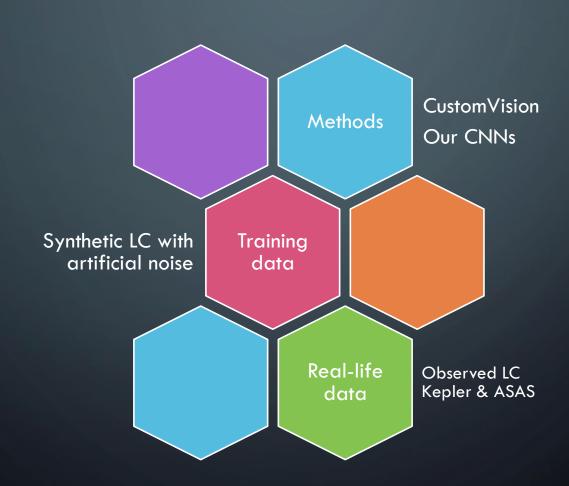
TOTAL

PARTIAL

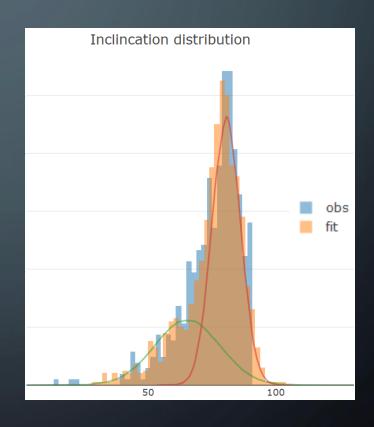




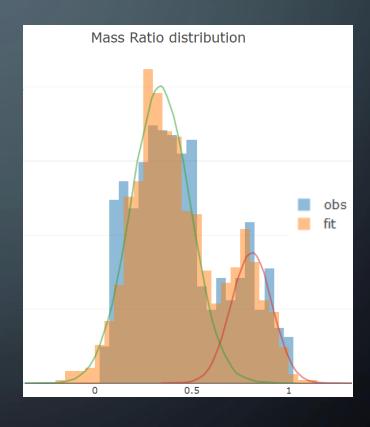
ADVENTURES WITH COMPUTER VISION



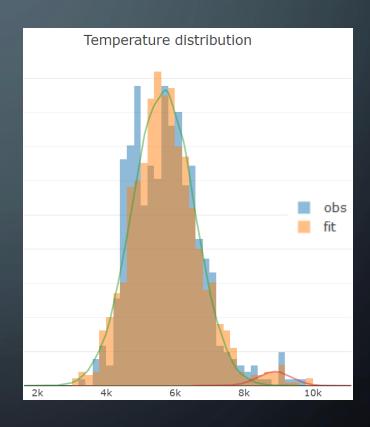
- Synthetic LCs
- Labels based on light contribution of eclipsed star
- Parameters sampled from observed distributions
 - Inclination
 - Mass ratio
 - Temperatures
 - Filling factor (radii)
 - Spot size & location



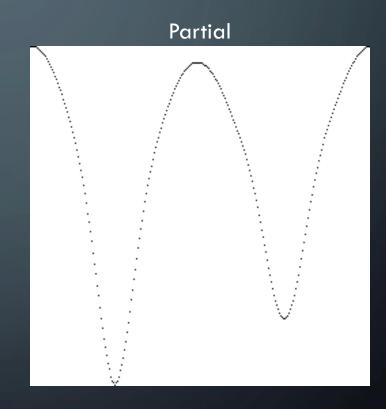
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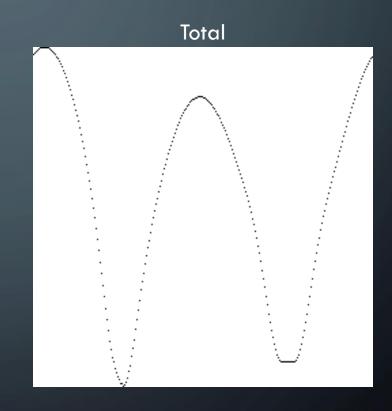
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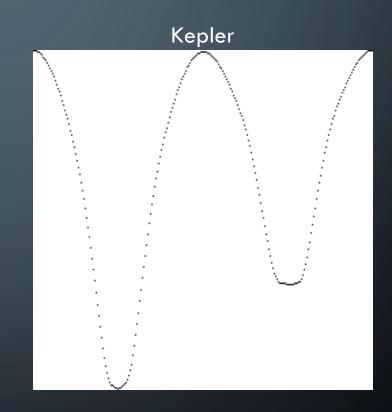
- No noise (0.00)
 Like space-based observations
- Moderate noise (0.02)
 Like ground-based
 observations with 1m class
 telescopes
- High noise (0.05)
 Like survey data from ASAS,
 CSS, OGLE etc.



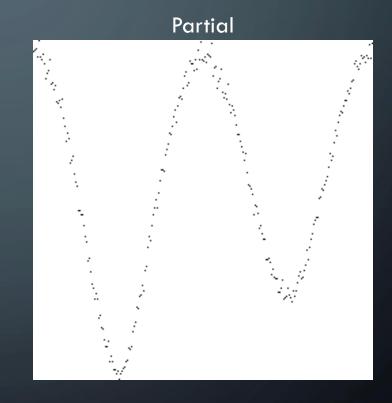
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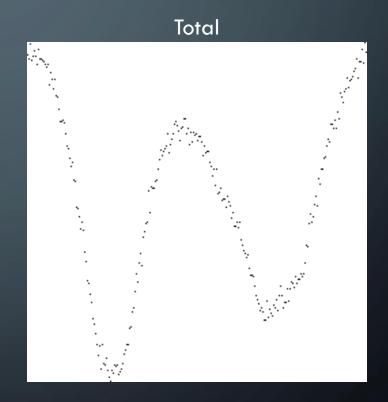
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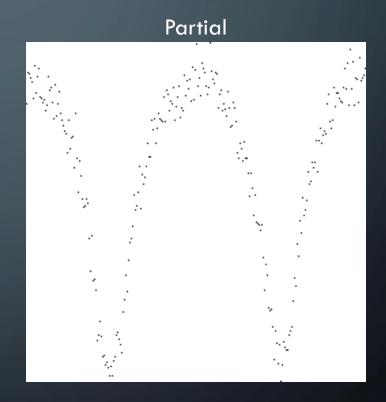
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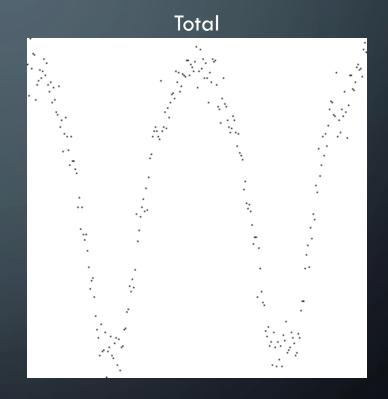
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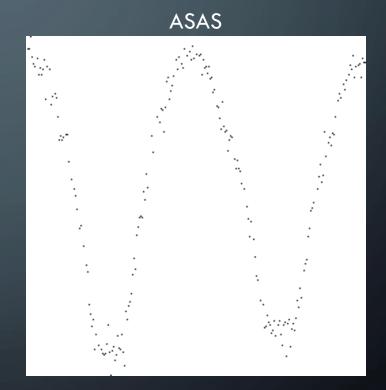
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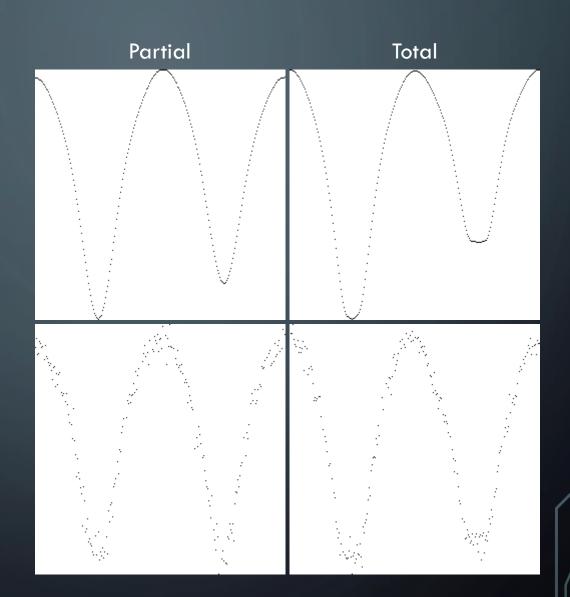
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TEST DATA

Kepler 300 LCs 45 total eclipses

ASAS 250 LCs 30 total eclipses



PROCESSING OF OBSERVATIONS

Phase-folding and aliasing to center the minima

Phase-shifting so the deeper minimum is always to the left

Outlier removal & amplitude normalization

Binning to match image size

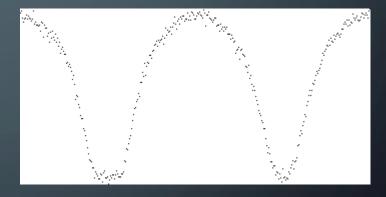
IMAGE SIZES WITH MODERATE NOISE



 100×100 (CNN10)



 250×250 (CNN15)



 350×175 (CNN15)

COMMERCIAL IMAGE RECOGNITION

http://CustomVision.ai

- Part of Microsoft Cognitive Services
- Free (with bandwidth restrictions)
- Pretrained model for transfer learning
- $F1 \approx 95\%$ on generated test data

CUSTOM-MADE IMAGE RECOGNITION

- Tools:
 - Keras on top of Tensorflow in Python
- Variants:
 - "CNN10"
 - "CNN15"

Layer	Output	Shape 	Param #
Conv2D		100, 100, 16)	160
MaxPooling2D	(None,	50, 50, 16)	0
Conv2D	(None,	50, 50, 32)	4640
MaxPooling2D	(None,	25, 25, 32)	0
Conv2D	(None,	25, 25, 64)	18496
MaxPooling2D	(None,	12, 12, 64)	0
Conv2D	(None,	12, 12, 64)	36928
MaxPooling2D	(None,	6, 6, 64)	0
Conv2D	(None,	6, 6, 64)	36928
MaxPooling2D	(None,	3, 3, 64)	0
Flatten	(None,	576)	0
Dense	(None,	512)	295424
Dense	(None,		513
 =================================	202.00	======================================	

Total params: 393,089 Trainable params: 393,089 Non-trainable params: 0

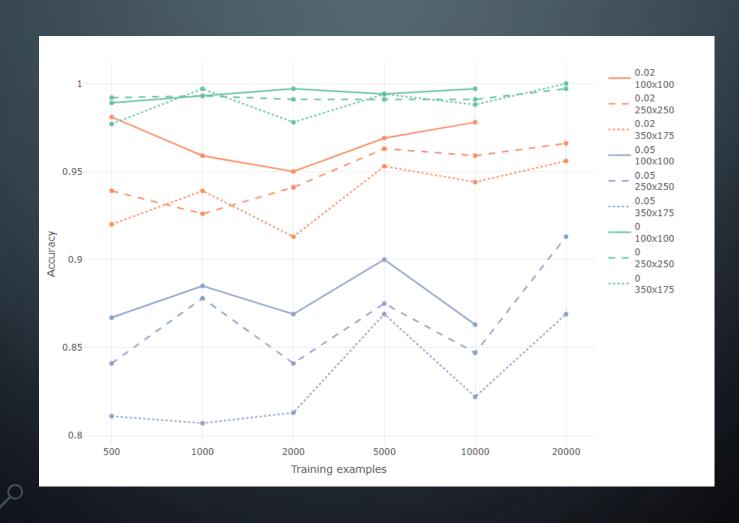
CUSTOM-MADE IMAGE RECOGNITION

- Tools:
 - Keras on top of Tensorflow in Python
- Variants:
 - "CNN10"
 - "CNN15"

Layer	Output Shape	Param #		
Conv2D	(None, 250, 250, 16)	160		
MaxPooling2D	(None, 125, 125, 16)	0		
Conv2D	(None, 125, 125, 32)	4640		
MaxPooling2D	(None, 62, 62, 32)	0		
Conv2D	(None, 62, 62, 64)	18496		
MaxPooling2D	(None, 31, 31, 64)	0		
Conv2D	(None, 31, 31, 64)	36928		
MaxPooling2D	(None, 15, 15, 64)	0		
Conv2D	(None, 15, 15, 64)	36928		
MaxPooling2D	(None, 7, 7, 64)	0		
Conv2D	(None, 7, 7, 64)	36928		
MaxPooling2D	(None, 3, 3, 64)	0		
Flatten	(None, 576)	0		
Dense	(None, 512)	295424		
Dropout	(None, 512)	0		
Dense	(None, 1)	513		
Total params: 430,017 Trainable params: 430,017				

Non-trainable params: 0

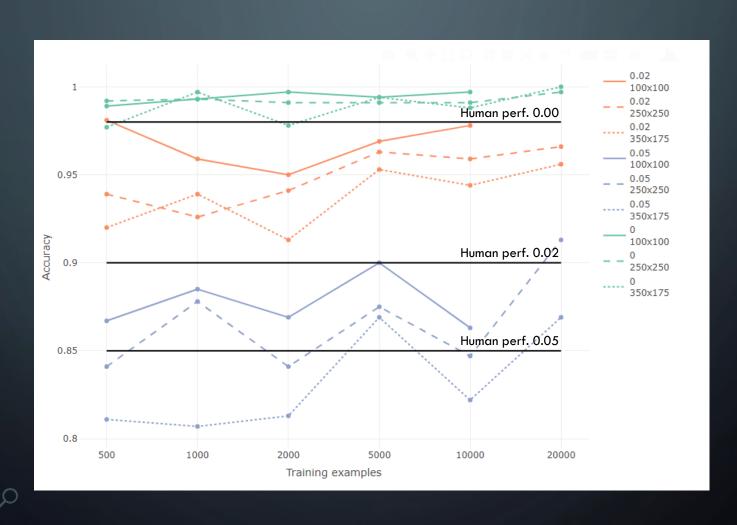
COMPARISON OF MODELS



TOTAL VS PARTIAL ECLIPSES HUMAN PERFORMANCE

Noise/	'Size	Balanced Accuracy	F1 Score
0.00		0.98	0.97
	250x250	0.96	0.96
	350x175	0.97	0.97
0.02	11111	0.90	0.85
	250x250	0.88	0.81
	350x175	0.92	0.90
0.05		0.85	0.75
	250x250	0.84	0.69
	350x175	0.85	0.81

COMPARISON OF MODELS



APPLICATION

Accuracy compared to human classification:

- Kepler 10 misclassifications out of 300 (Acc $\approx 97\%$)
- ASAS 23 misclassifications out of 250 (Acc $\approx 90\%$)
 - But very bad recall $\approx 10\%$

INSIGHTS

- Recognizing total eclipses in noisy data is a hard problem both for humans and for machines
- Models get in trouble with overfitting when training with noisy data
 - Dropout & regularization only have merit with large training sets
- Training on noisy data doesn't improve performance

RESOURCES

- Azure Machine Learning Studio studio.azureml.net
- Deep Learning Specialization online courses
 www.coursera.org/specializations/deep-learning
- TensorFlow in Practice Specialization online courses
 www.coursera.org/specializations/tensorflow-in-practice
- Machine Learning Yearning, a book by A. Ng