Deep learning stellar populations

László Dobos[1], Emese Forgács-Dajka[2], Szilvia Karsai[2],
Dezső Ribli[1] and István Csabai[1]

Eötvös University, Dept. of Physics of Complex Systems
Eötvös University, Dept. of Astronomy

Wigner GPU day, June 2, 2016

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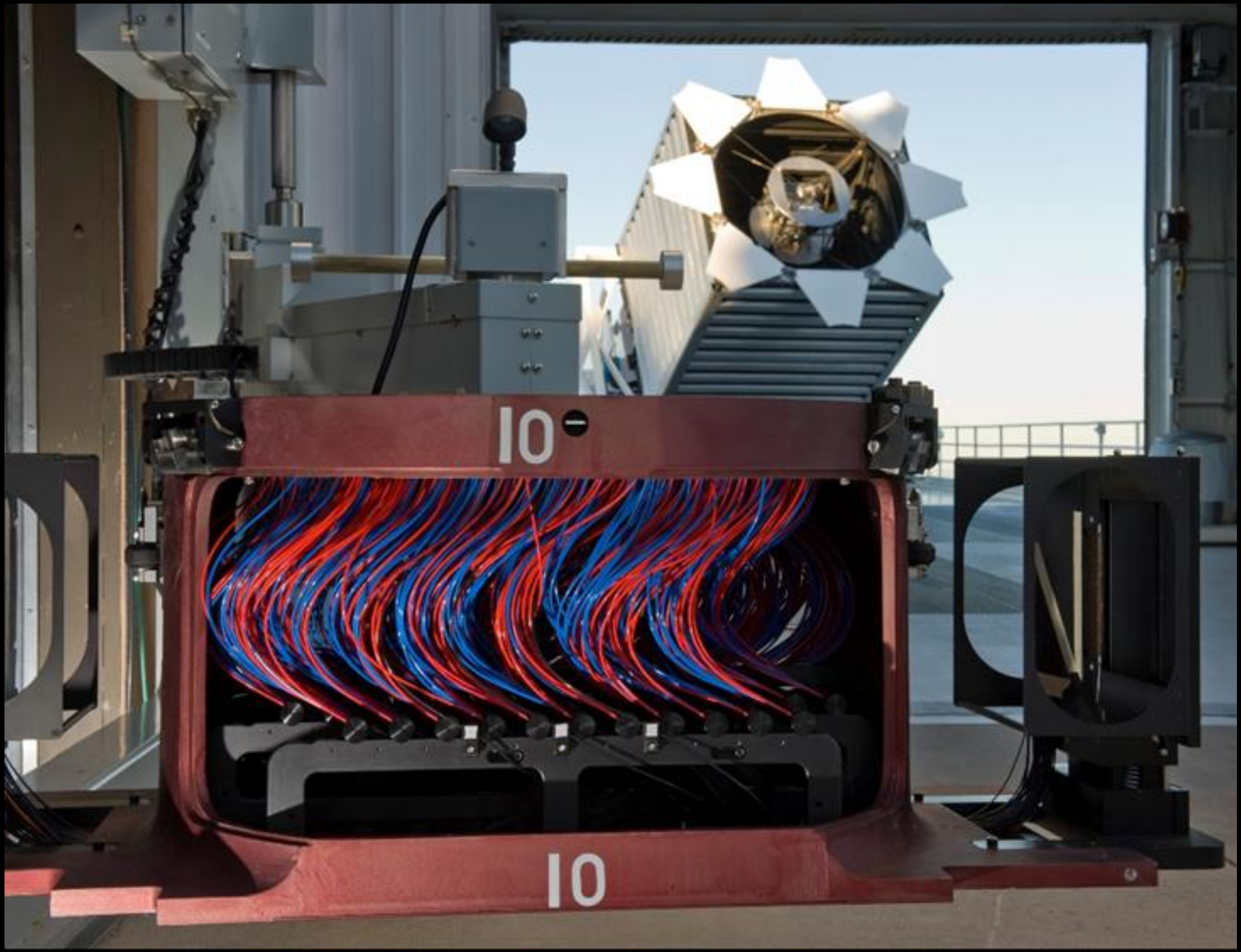
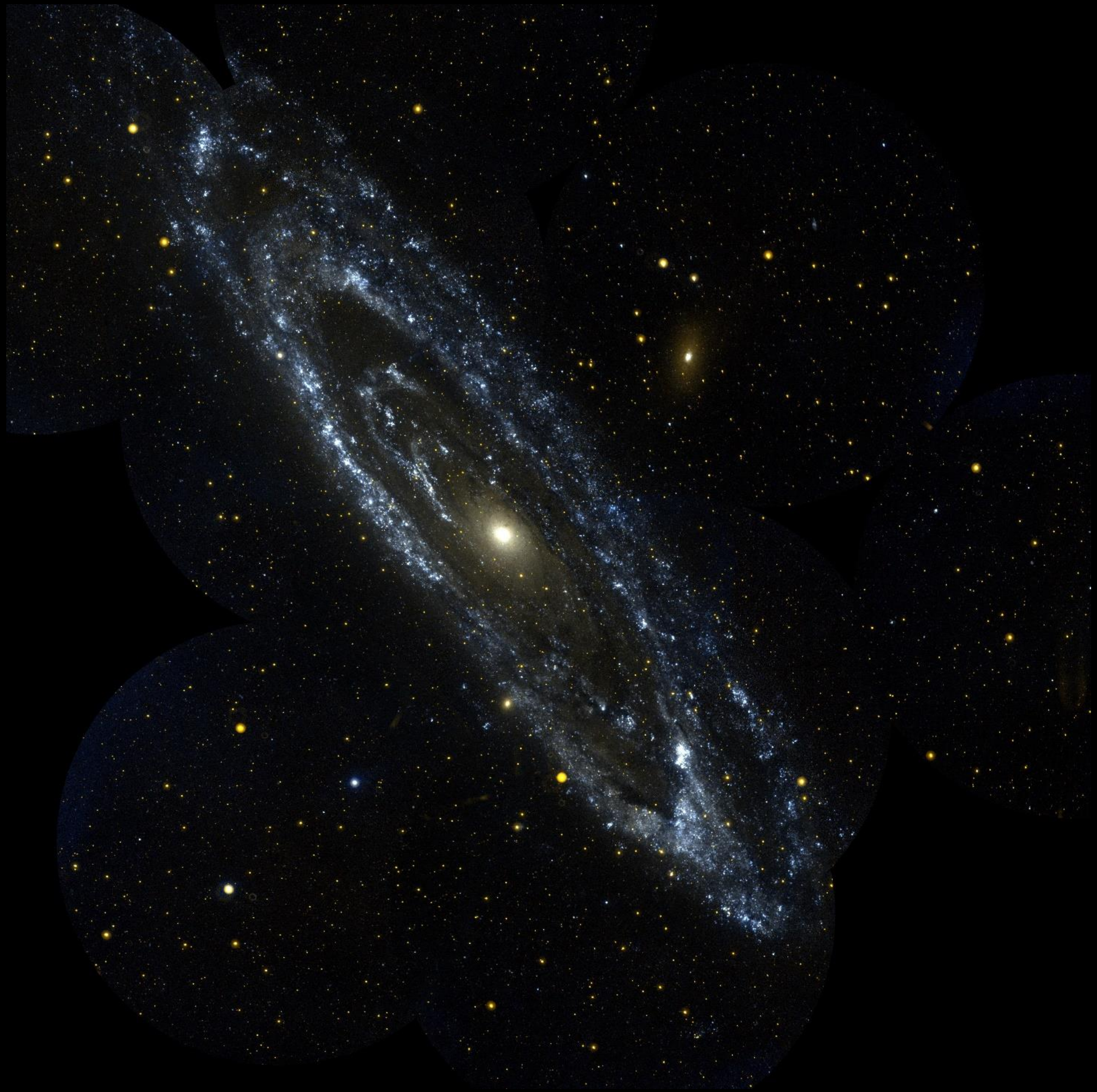
Galaxy spectra

- Fiber optic spectroscopy
  - Sloan Digital Sky Survey
  - Anglo-Australian Telescope
  - LAMOST
- 1M+ galaxy spectra available
- Medium resolution: 0.5 – 2 Å
- Redshift
- Galaxy physical properties



Physical properties of galaxies

- Stellar populations
- Metallicity
- Gas and dust content
- Stellar mass
- Orbital velocities
- Dynamical mass
- Mass to light ratio
- Dark matter content
- Star formation rate and history
- Mean stellar age, galaxy age
- Star formation episodes
- Nuclear activity



Stellar Population Synthesis

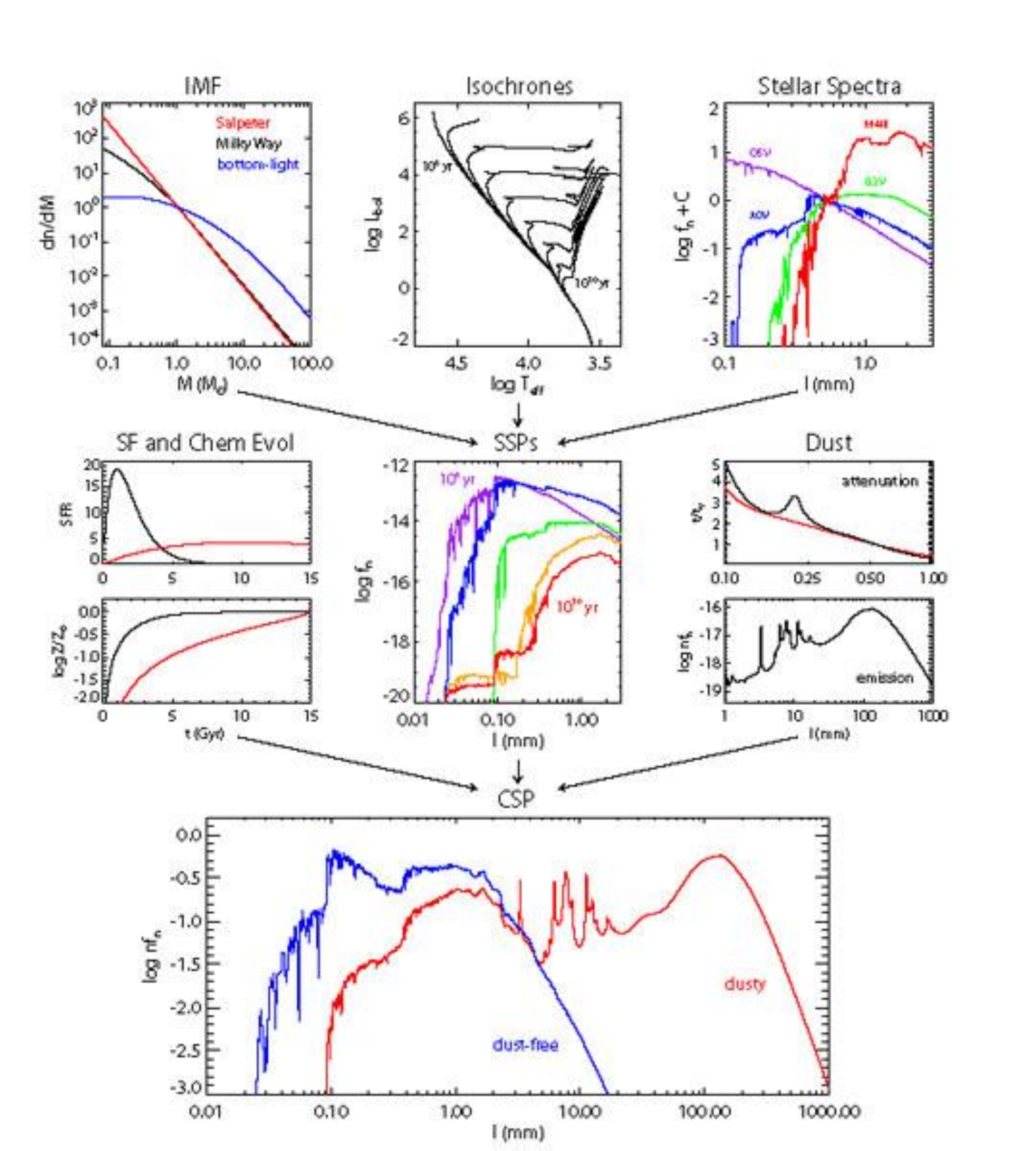
- Theoretic approach to model spectra

- Single stellar populations: S_{SSP}
  - Stars from the same cloud, aging together

- Star formation history: $\Psi(\tau)$
- Composite stellar populations: $S_{\text{galaxy}}(t)$

- Fitting models is a deconvolution of $\Psi(\tau)$

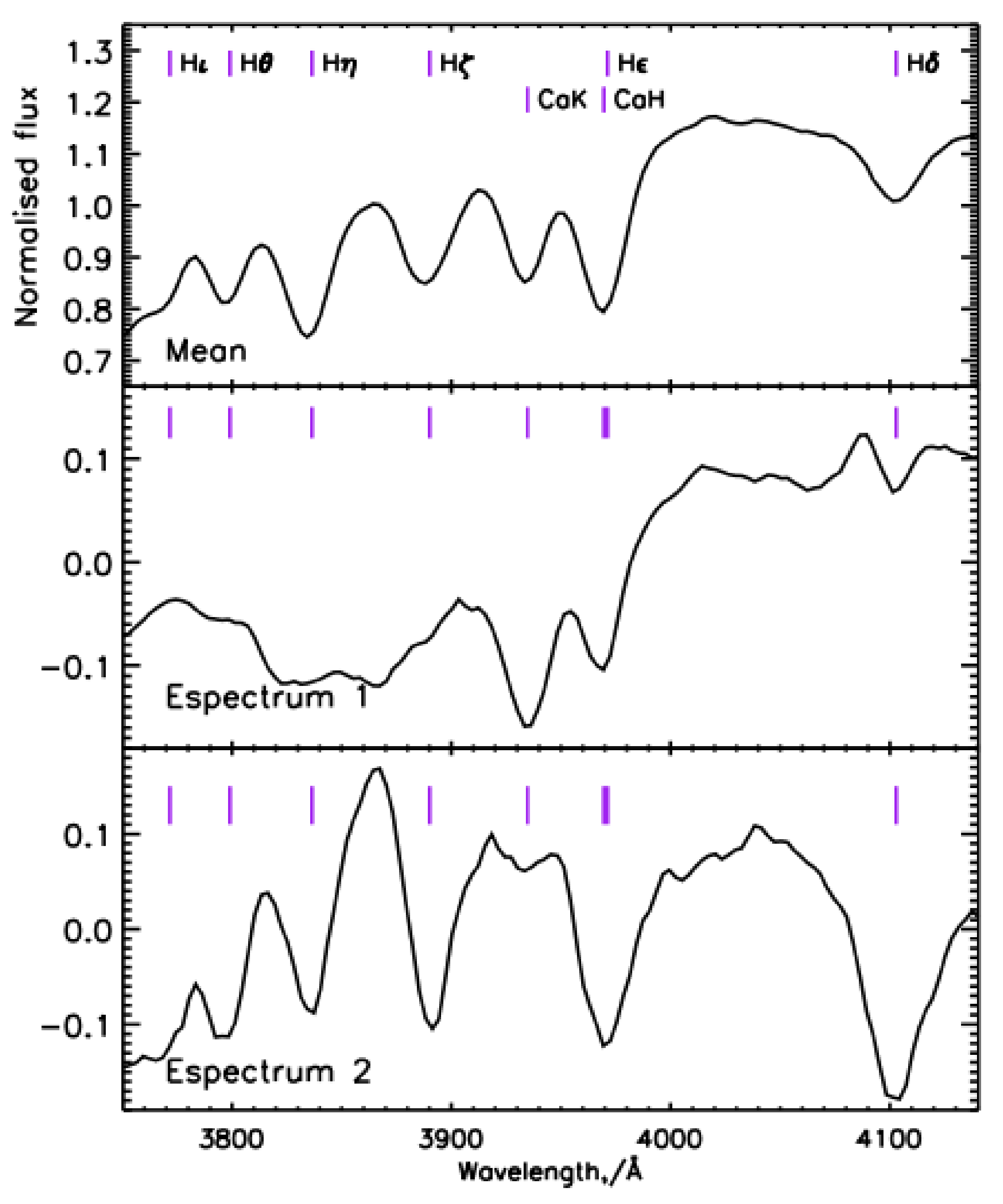
$$S_{\text{galaxy}}(t) = \int_0^t S_{\text{SSP}}(t-\tau)\Psi(\tau)\mathrm{d}\tau$$



Conroy, Annu. Rev. Astron. Astrophys. 2013. 51:393-455

Empirical approaches

- Continuum indices
  - Absorption line properties well correlate with physical parameters
- PCA
  - Expand spectra on eigenbasis
  - Principal components correlate with physical parameters
  - Works well with noisy data and gaps
  - Not all parameters can be recovered
- MOPED
  - Dimensionality reduction method similar to PCA



Wild et al. 2009 MNRAS Vol. 395, Issue 1, pp. 144-159.

Direct model fitting

- **Stochastic burst libraries**

- Generate many model spectra with a wide range of parameters
- Find best-fitting model in library
- Allows for parameter priors

- **SPSFast**

- Dezső Ribli et al.
- Super fast computation of composite spectra on the GPU
- Allows for direct fitting with MCMC
- Parameterizing star formation history is still a problem

Deep learning on the GPU

- Half a day of
  - System setup
  - Building from source
  - Configuration
- 50 lines of python code to train

K KERAS

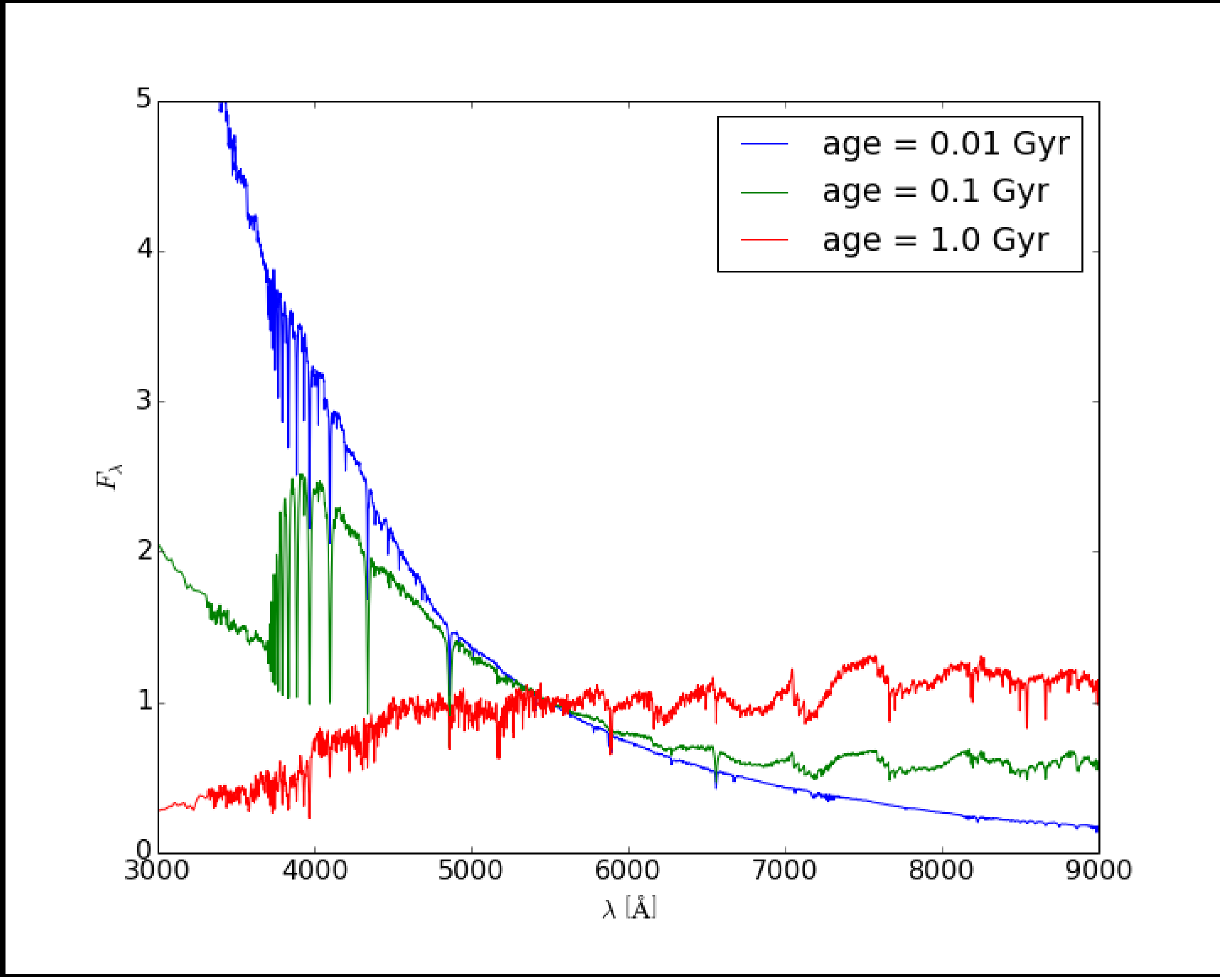
theano

cuDNN

Galaxy age

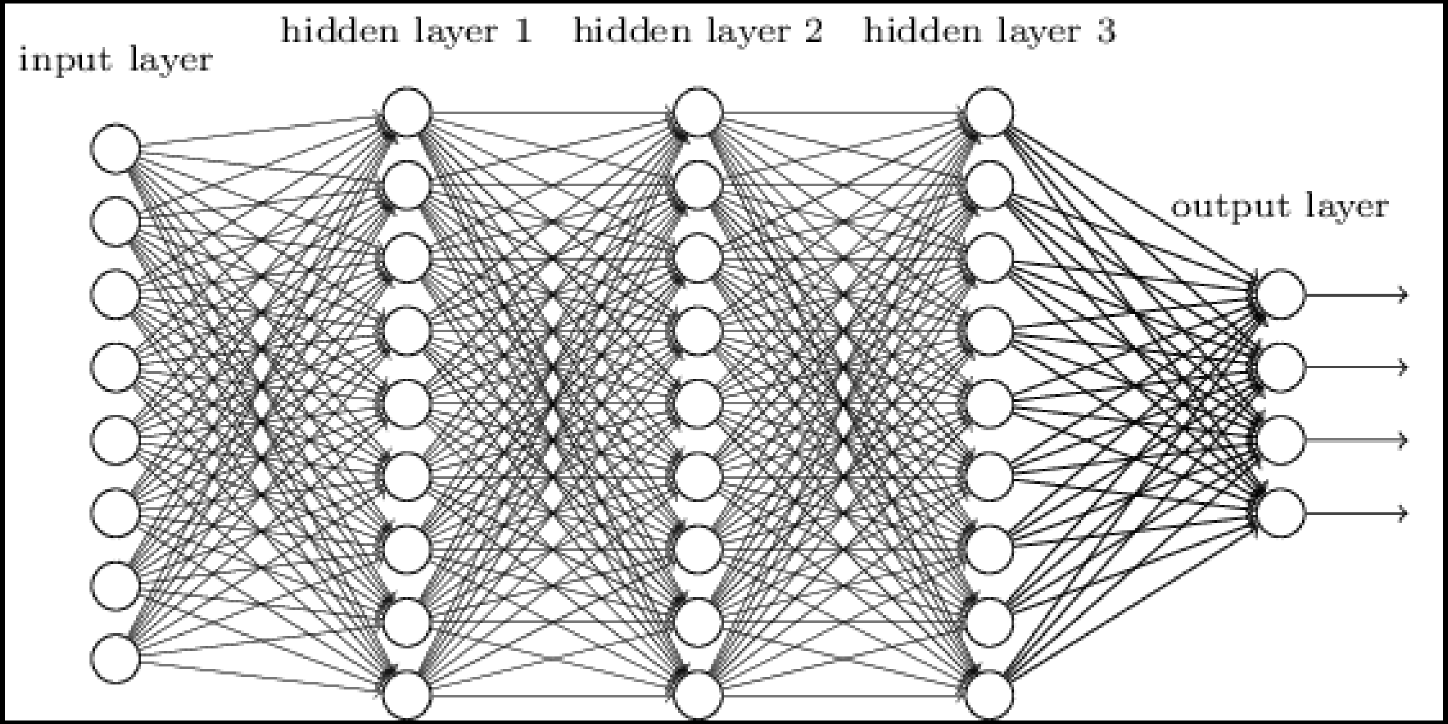
- Age predicted from overall shape
- Use dense network

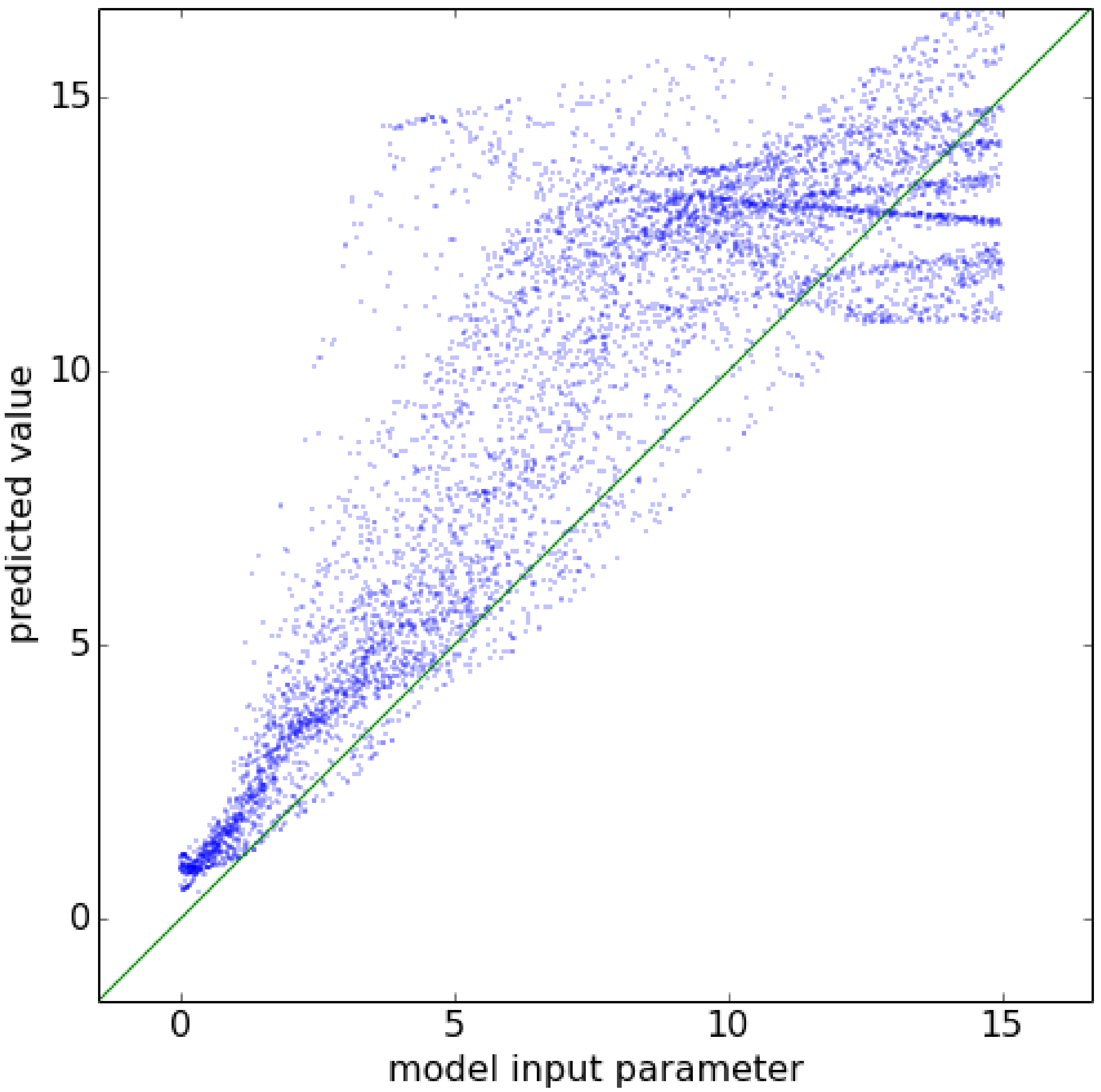
- Young stellar populations evolve faster
- Spectrum depends on log-age
- Expect better fit for age < 1 Gyr



Dense neural networks

- Hidden nodes: full interconnect
- Independent weights
- Learn global features





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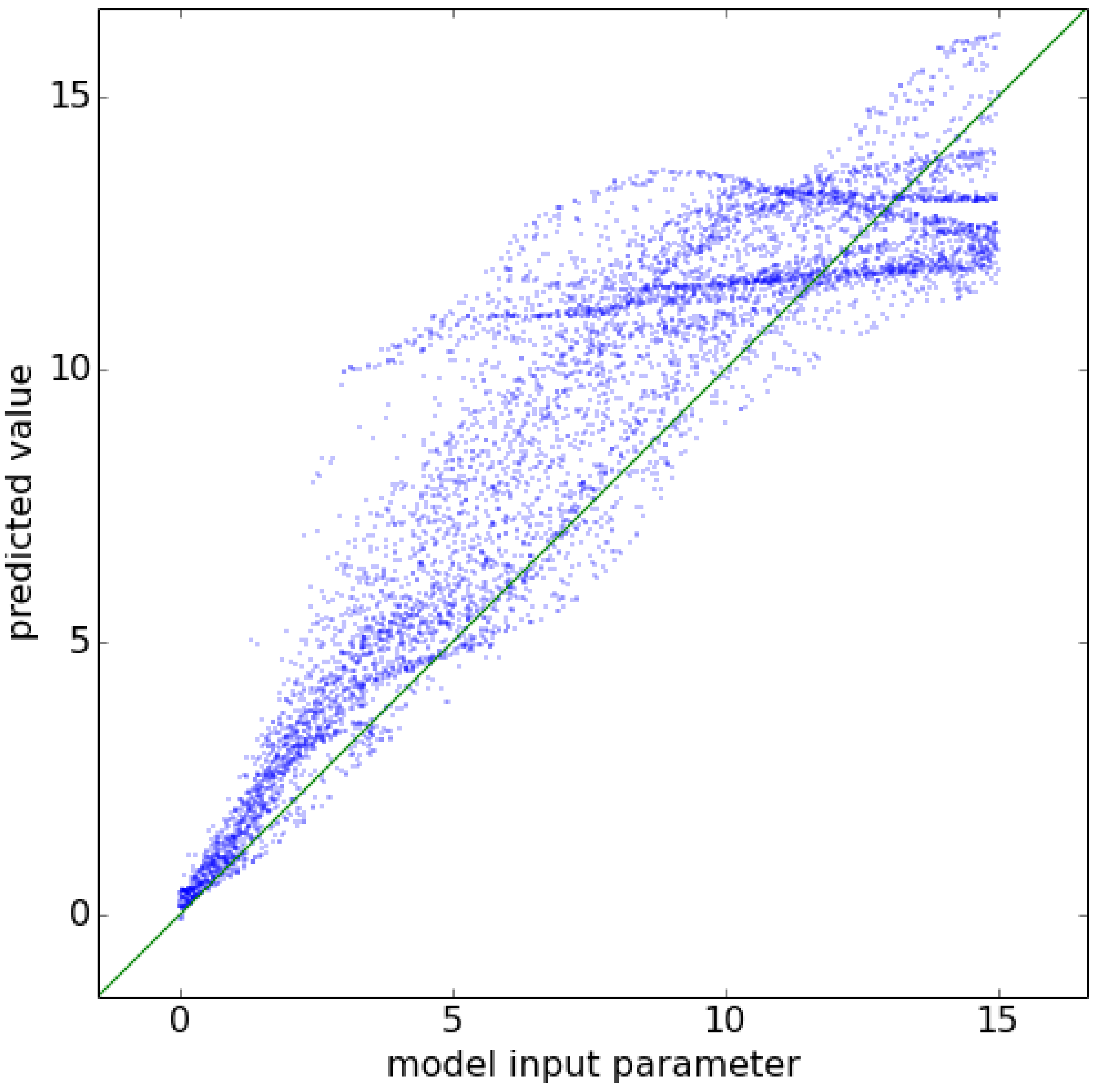

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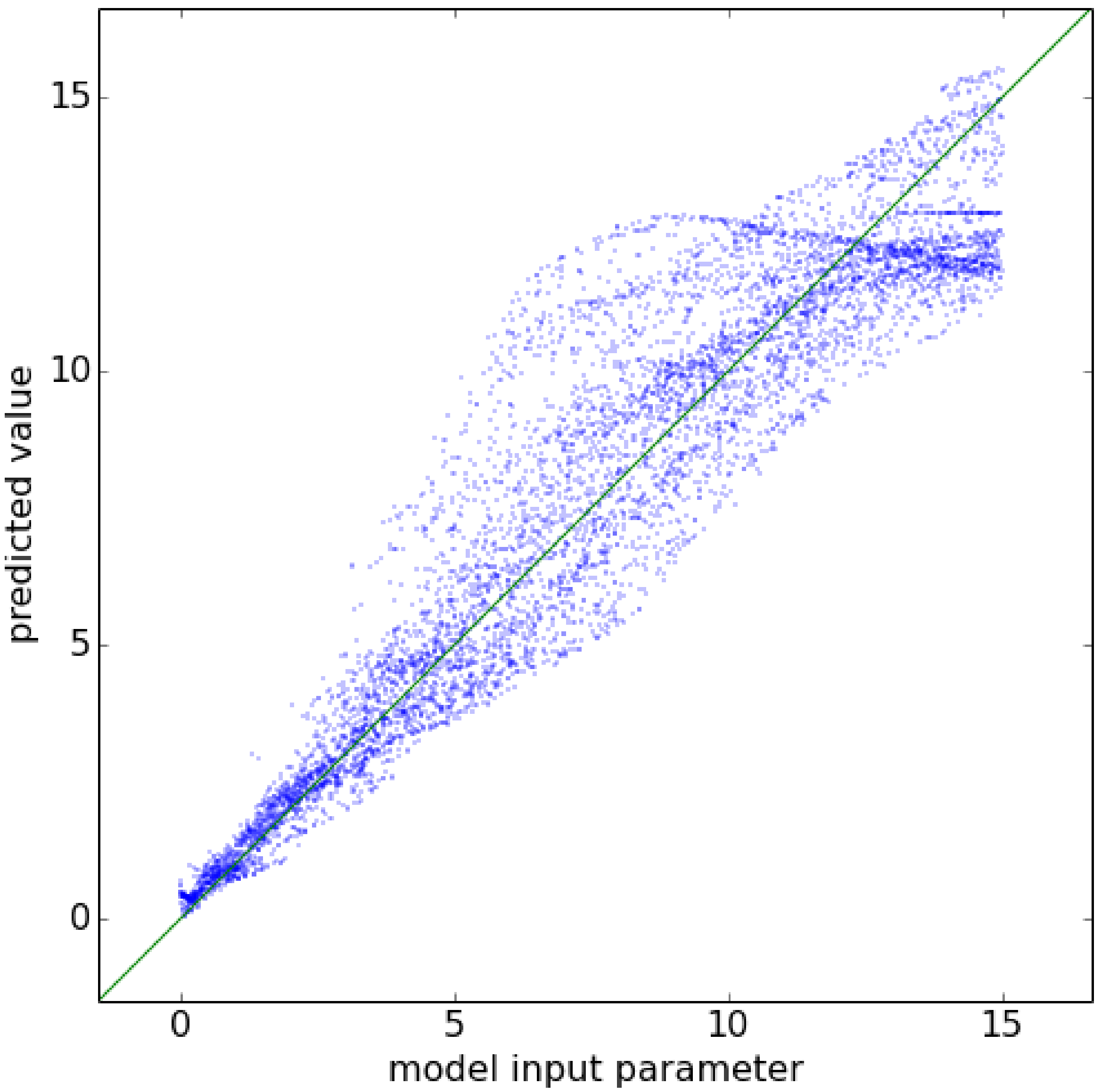

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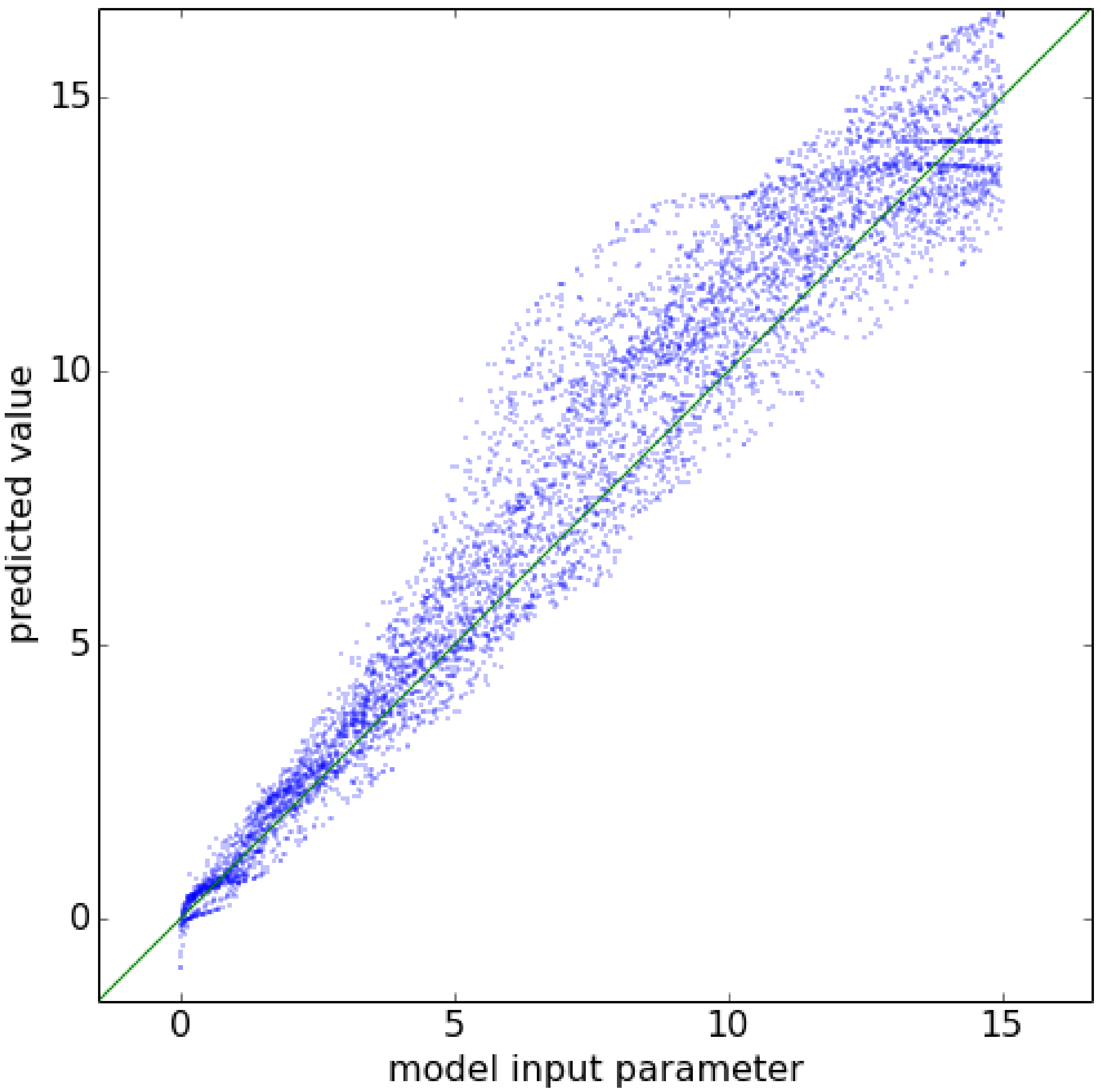

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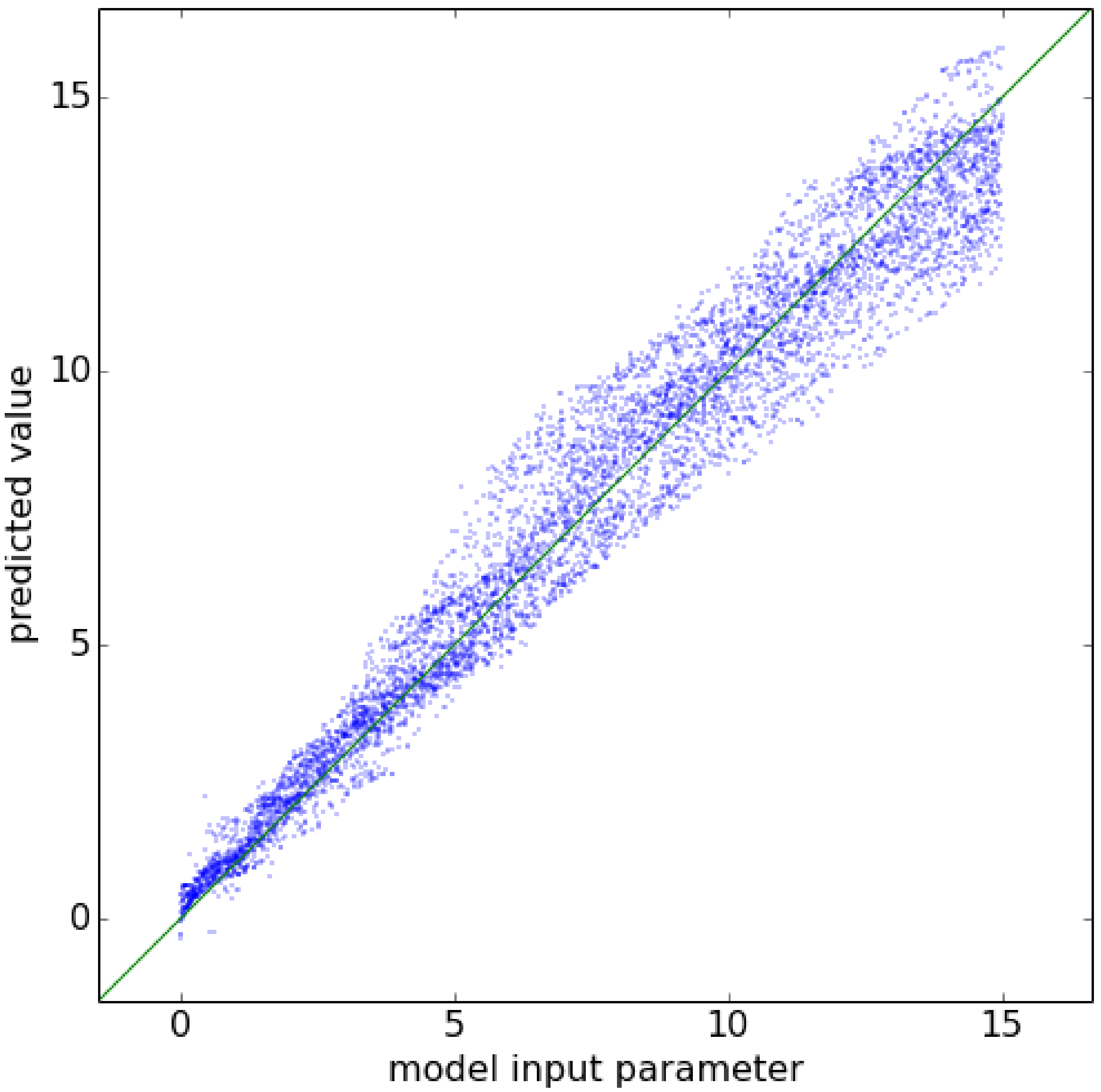

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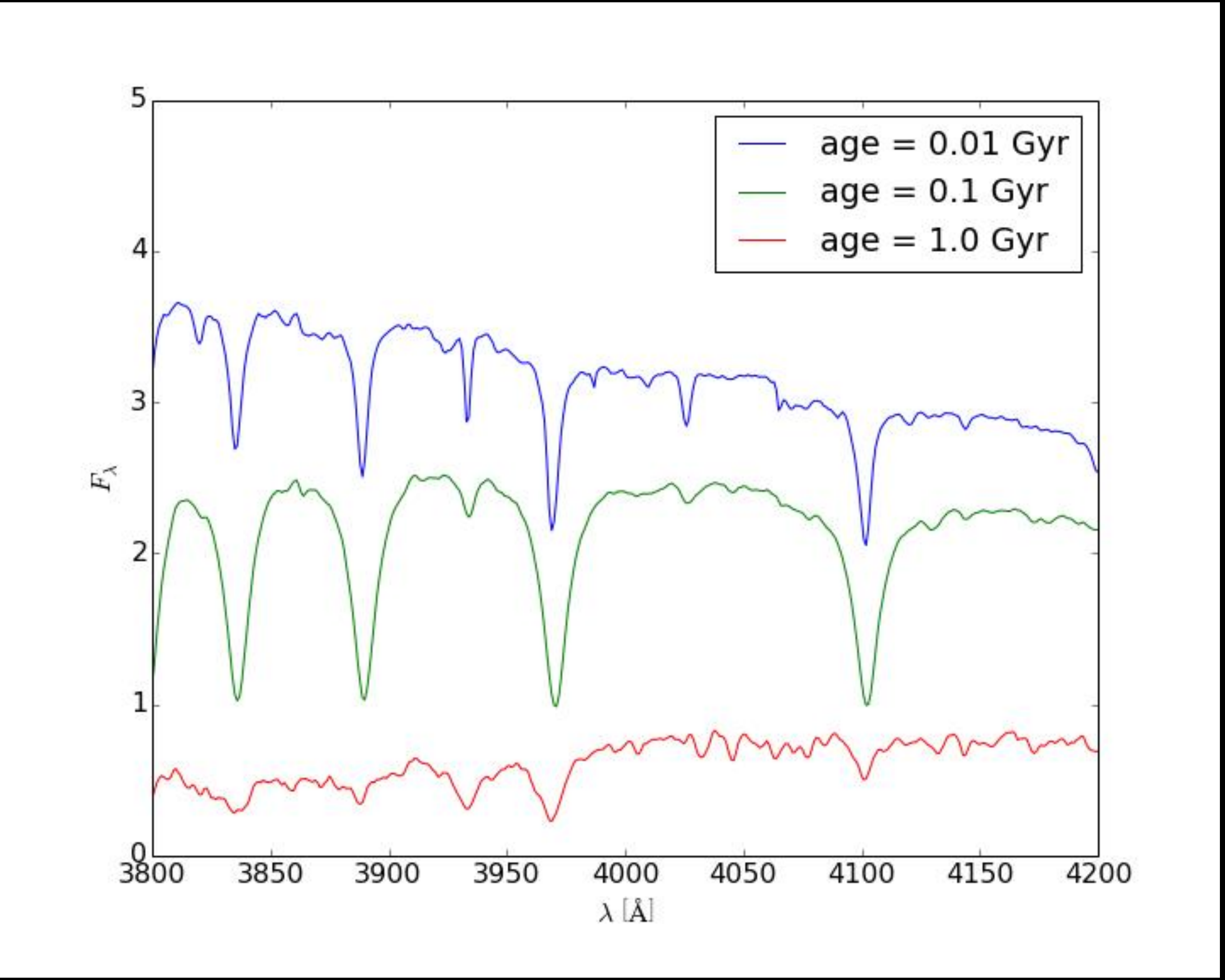
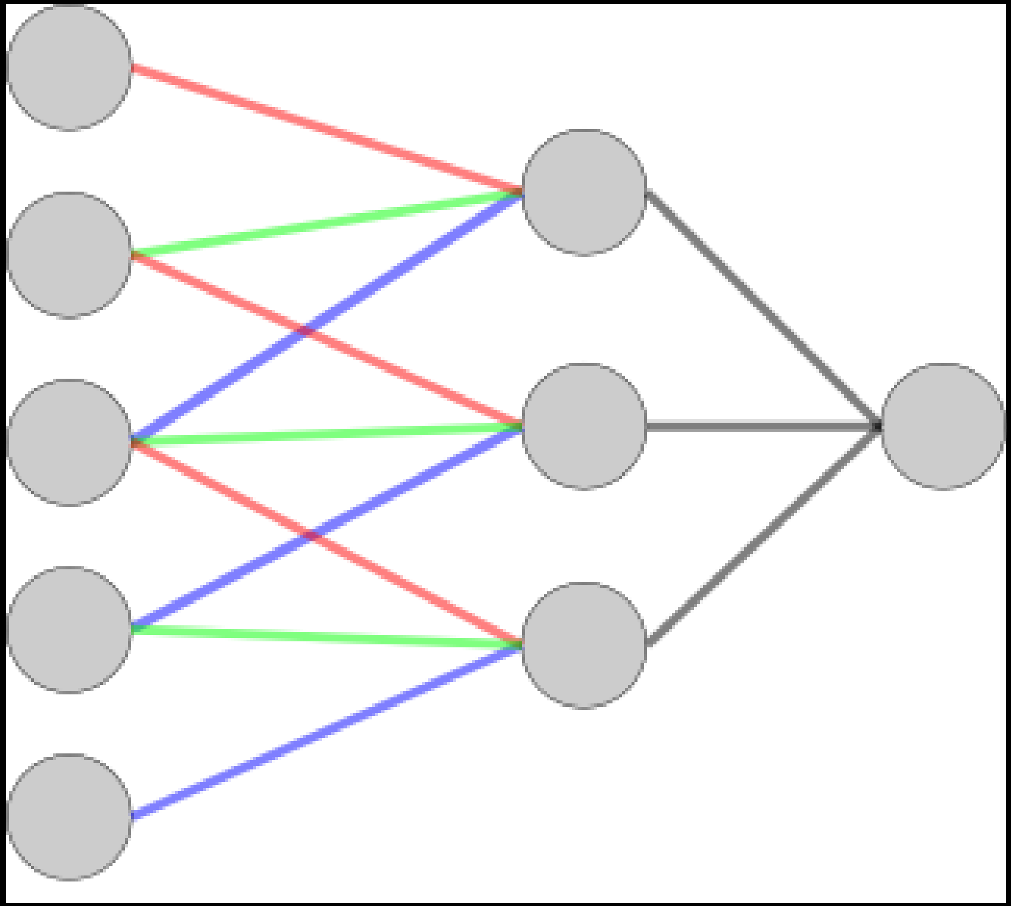
Metallicity

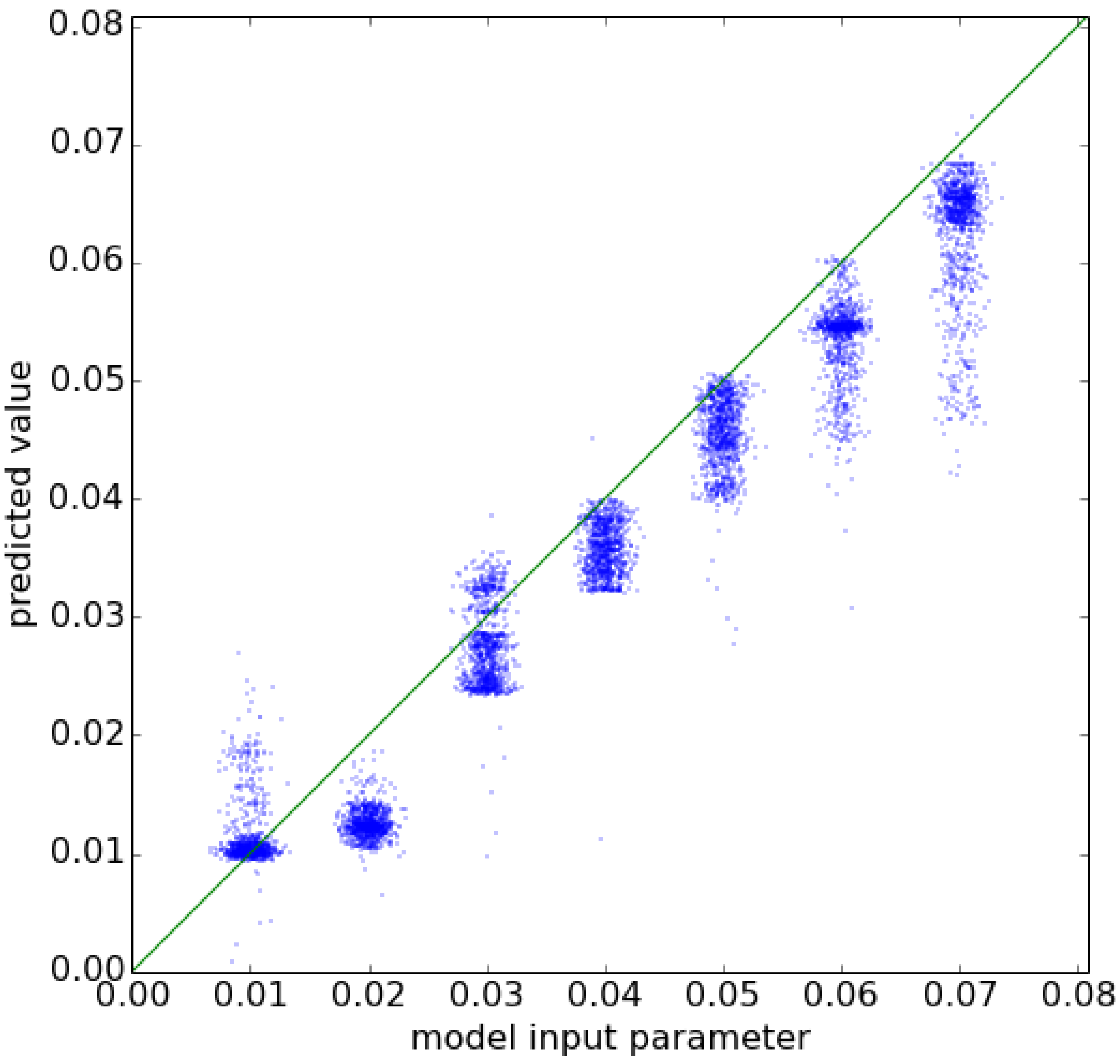
- Heavier elements in stellar atmospheres
- Spectral degeneracy:
  - Effect on continuum similar to age
- Focus on absorption lines
- Use convolutional networks



Convolutional neural networks

- Weights of spatially close edges are kept the same
- Local focus
- Repeating pattern: kernels
- Propagate many kernels up





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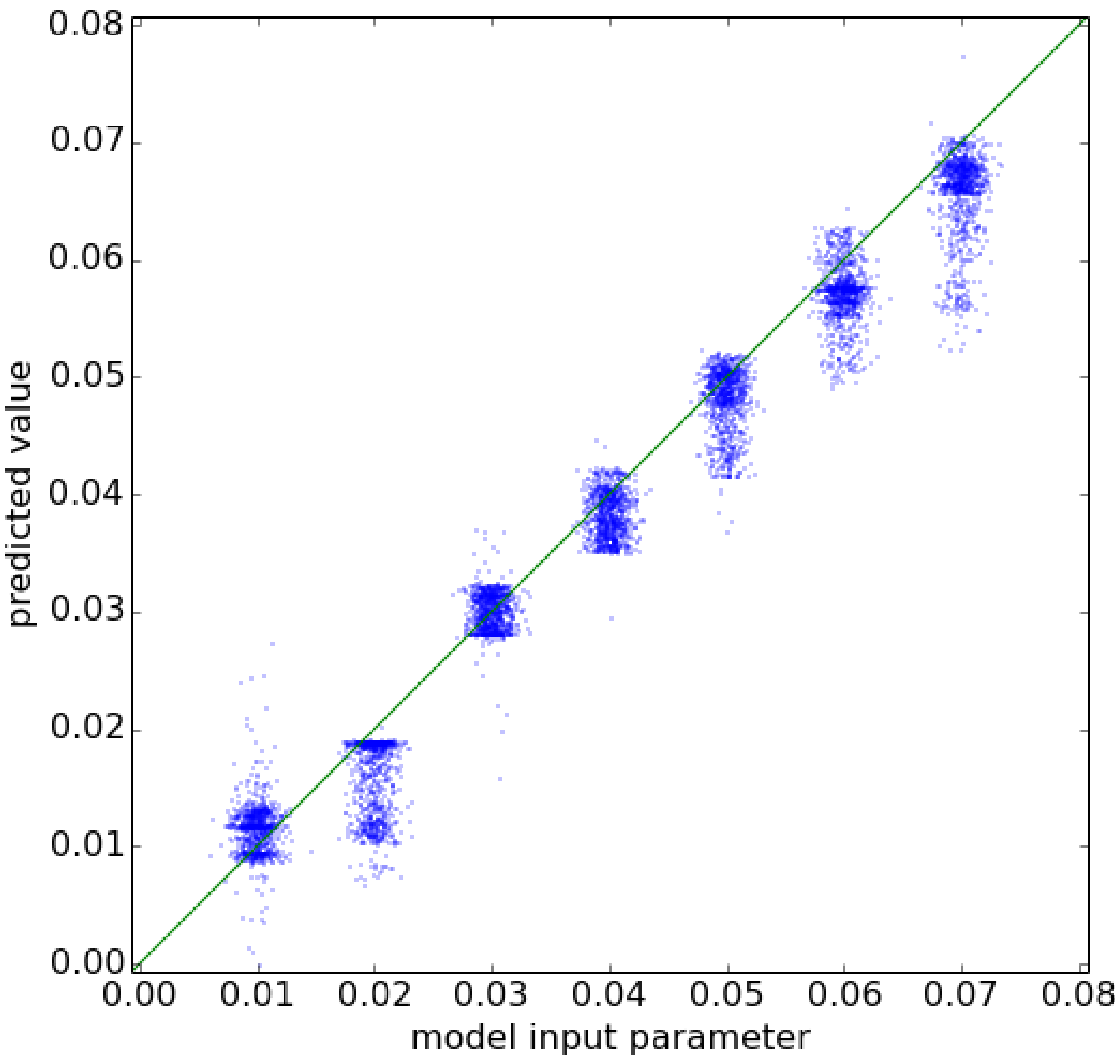
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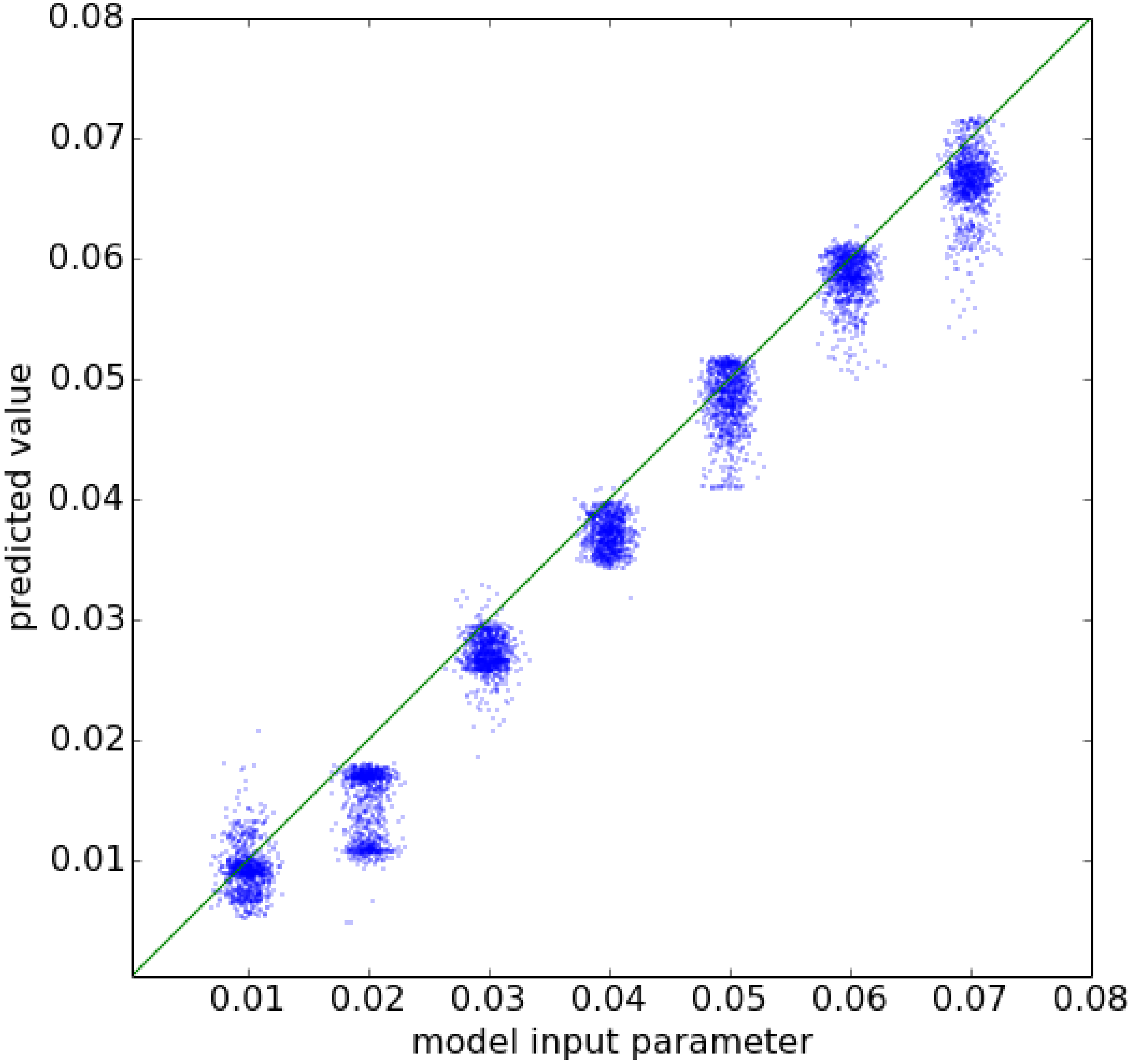

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Conclusions & future work

- Deep Neural Networks can tell physical parameters from spectra
- Excellent tool for reliable mass processing of spectra

- Need to teach on realistic models
- Account for real-line noise and drop outs
- Compare with traditional methods