Constraining dust mineralogy from mid-IR spectra

Peter Scicluna

ASIAA, Taiwan

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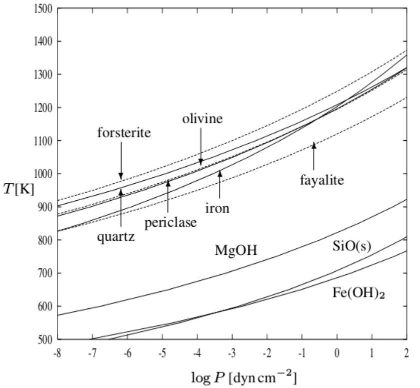
Ciska Kemper, Sundar Srinivasan, Lapo Fanciullo, Alfonso Trejo, Thavisha Dharmawardena, Jonty Marshall (ASIAA), Sacha Hony (Heidelberg)

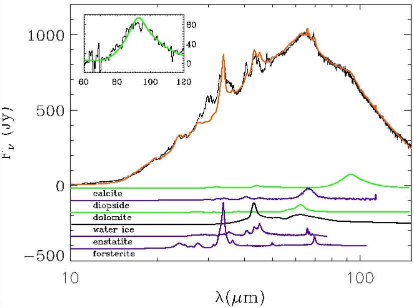
Why do we care?

- Traces physical conditions in dust-forming region
- History of dust processing
- Mineralogy determines optical properties, important for wind driving



Identifying minerals

- Observe features and match with lab data.



Kemper et al, 2002b

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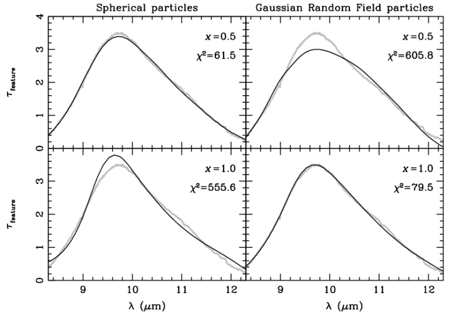
  - Grain size and shape



Min et al, 2005

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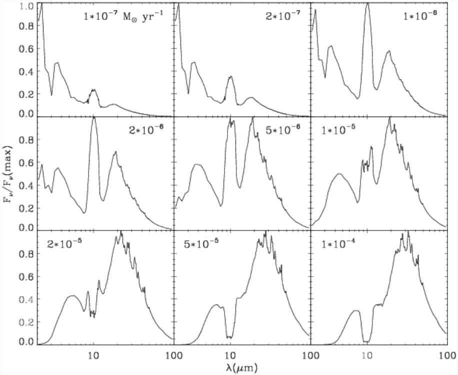

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Identifying minerals

- Observe features and match with lab data.
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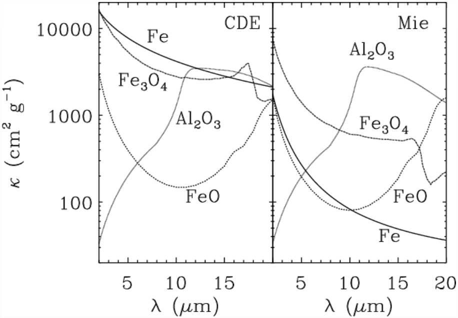
  - not everything has features!



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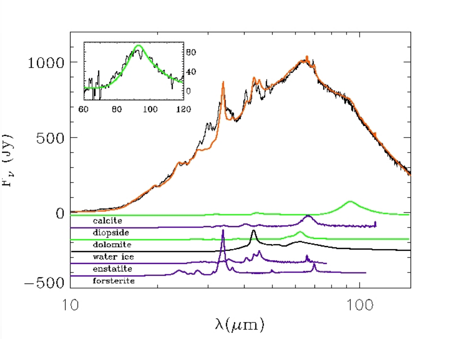

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Abundances?

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- Individual sources or small samples
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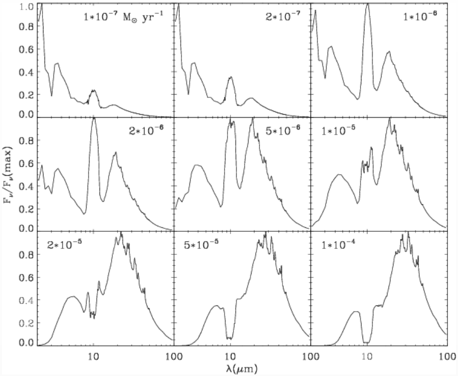
- Many confounding factors
  - RT effects,
  - grain shape
  - variability
  - ...



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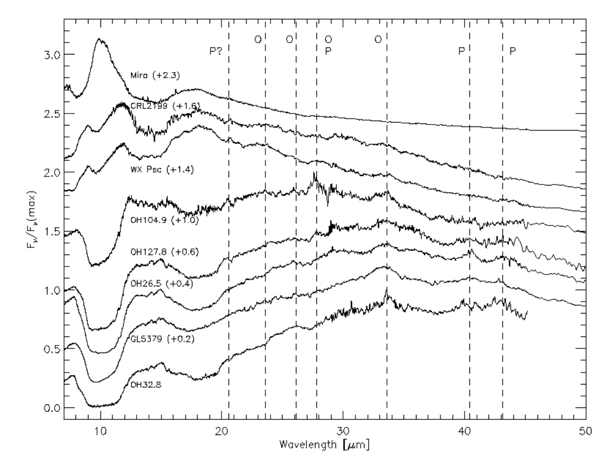
Previous attempts

e.g Sylvester et al., 1999



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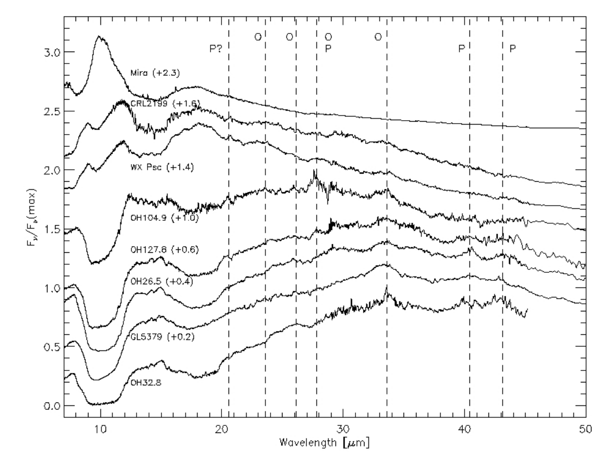
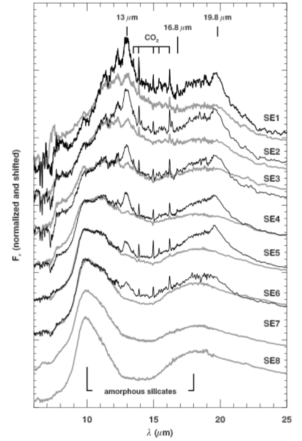


Sloan et al., 2003



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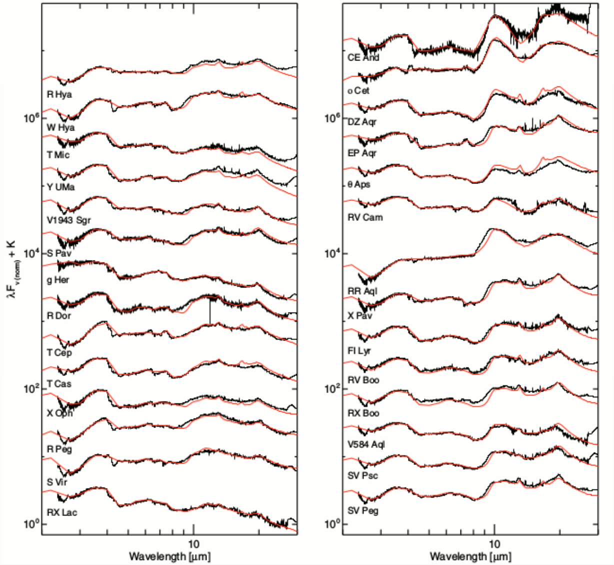

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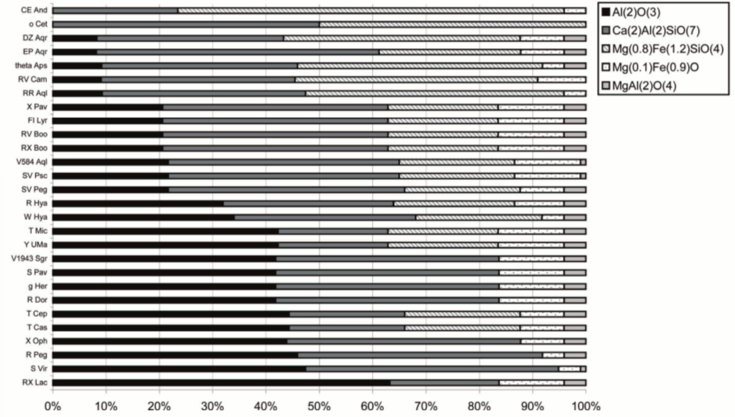

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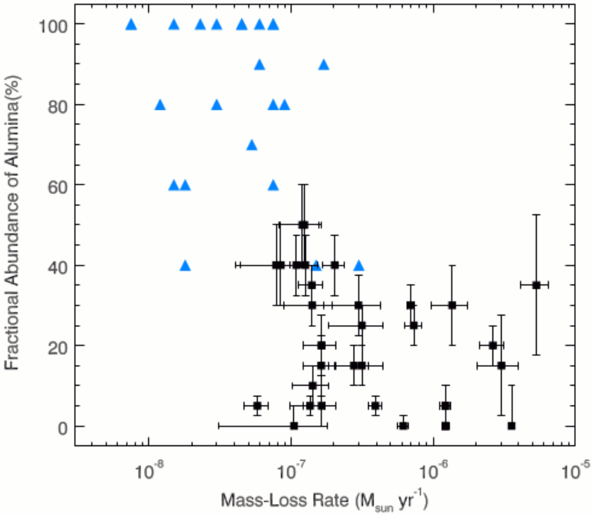
Jones et al., 2014



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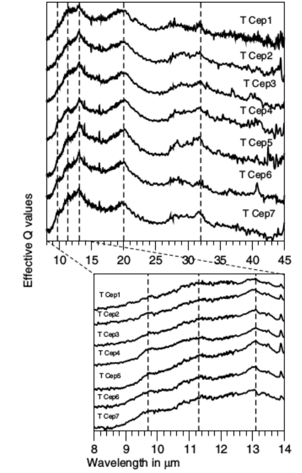

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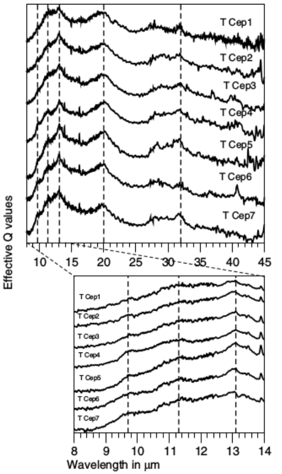

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  - Or grids, sampling often too sparse

AMPERE: A new framework

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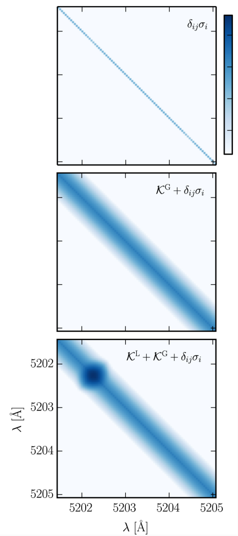
- Also for scientific issues - variability, imperfect model (not all species, no atomic lines etc), foreground extinction
- Can use interpolation if model expensive (e.g. STARFISH, Czekala et al., 2015)

Modelling data

- Model covariance matrix to encapsulate noise
  - Simple but effective
  - Plenty of literature
- Simple additive and multiplicative terms for calibration

"Keep it simple stupid" – Kelly Johnson



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Current/future capabilities

- Synthetic photometry, spectra
  - Global covariance structure
- Optimisation with emcee
- simple analytical models
- ideas and contributions are welcome!

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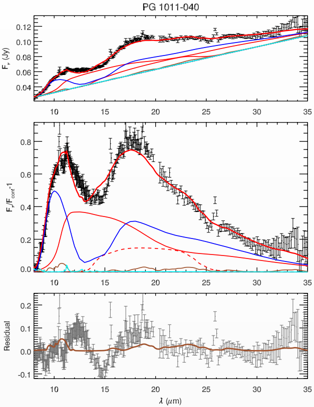
- Synthetic photometry, spectra, *visibilities, images*
  - Global covariance structure, *non-stationary covariance*
- Optimisation with emcee, *parallel genetic algorithm, +more*
- simple analytical models, *interfaces to common RT codes*
- ideas and contributions are welcome!

Current work

Replicating Srinivasan et al. (2017) - mineralogy of AGN winds.

Sundar's results:



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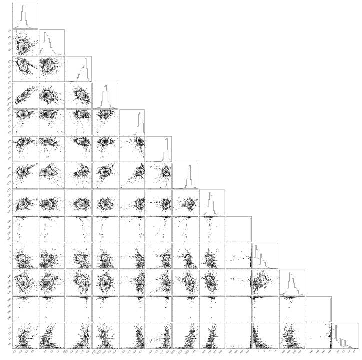

"Best fit" is consistent, but uncertainty is $\gtrsim$ 20%

Definitely not Gaussian

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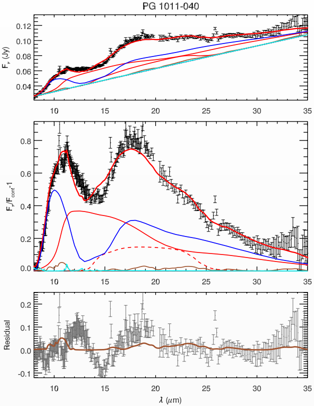

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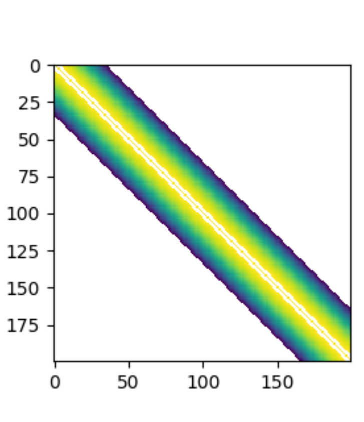

"Best fit" is consistent, but uncertainty is $\gtrsim 20\%$

Simple covariance model, correlated uncertainties are small

Summary

- Mineralogy
  - Critical to understanding dust formation and processing
  - Many components known, but abundances are not
- Major obstacles are methodological
  - Fitting heterogeneous data
  - variability, correlated uncertainties, etc
- AMPERE is designed to tackle these issues
  - forward modelling
  - model covariance ⇒ optimum weighting
  - understand distributions of solutions
- Code will be public
- Input and contributions are welcome!