

Bayesian Modeling for Type Ia Supernova Data, Dust, and Distances



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iCHASC
Astrostatistics Seminar
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Outline

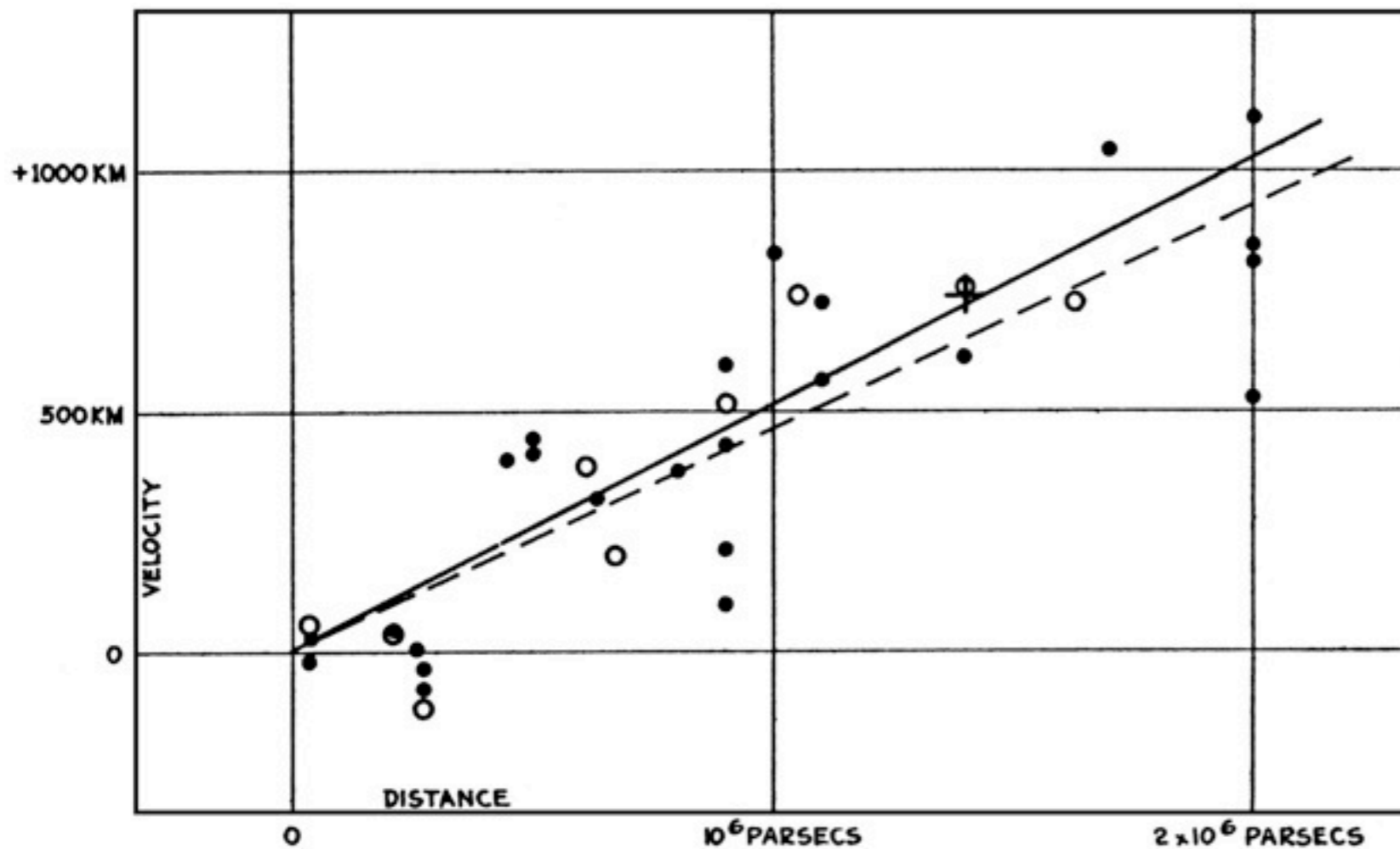
- Brief Introduction to Type Ia Supernovae & Cosmology
- Part I: Supernova Classification with Host Galaxy Data
- Part II: Hierarchical Bayesian Regression Model for SN Ia colors and spectroscopic velocities

SN Ia Basics:

Estimating Astronomical Distances with Standard Candle Principle

1. Know or Estimate Luminosity L of a Class of Astronomical Objects
2. Measure the apparent brightness or flux F
3. Derive the distance D to Object using Inverse Square Law: $F = L / (4\pi D^2)$
4. Optical Astronomer's units: $m = M + \mu$

The Expanding Universe: Galaxies are moving apart! Hubble's Law (1929)



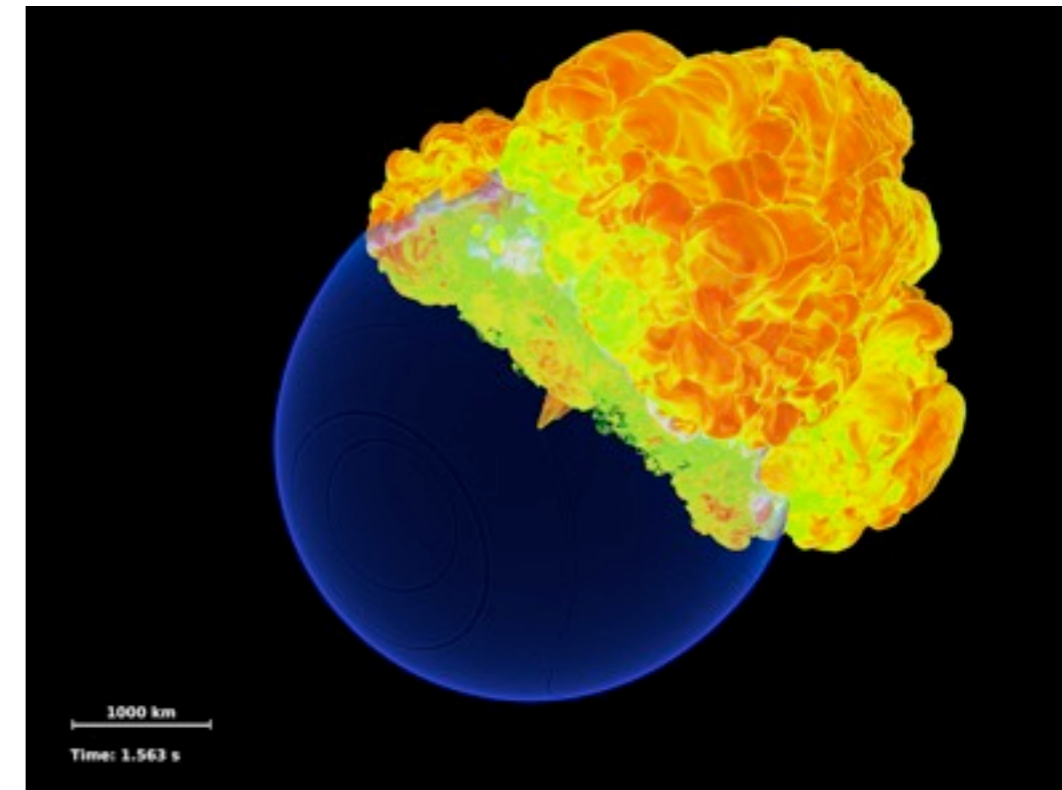
Hubble: @Einstein,
you're wrong

Distance \propto Velocity (Redshift)

But what is the rate of change of the expansion?
(the deceleration parameter)

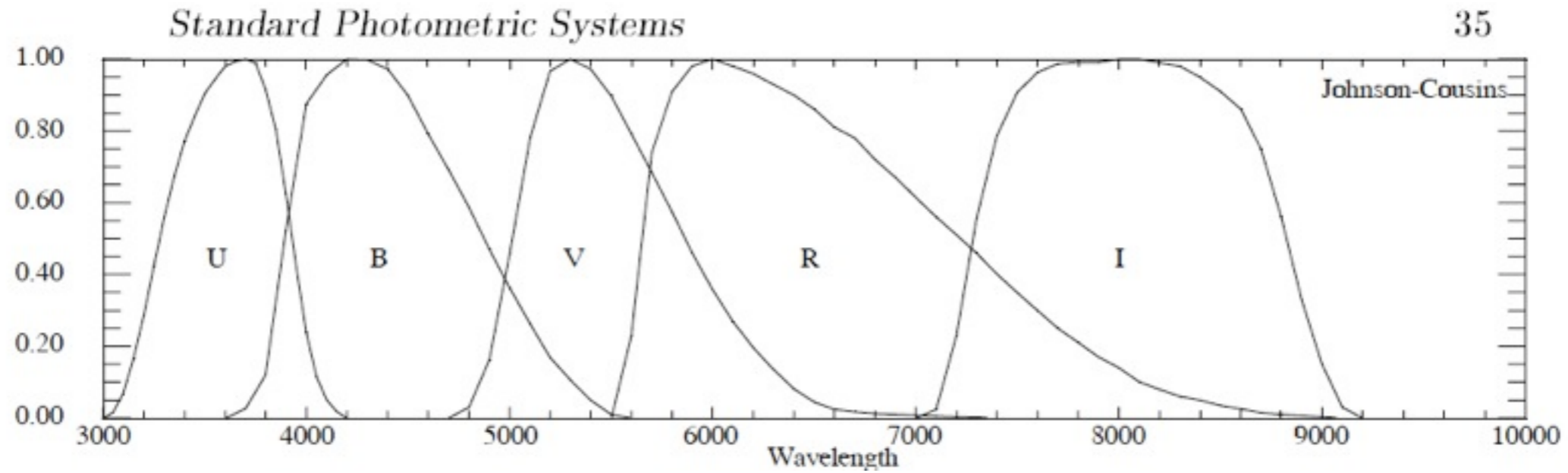
Type Ia Supernovae are Almost Standard Candles

- Progenitor: C/O White Dwarf
Star accreting mass leads to instability (single / double degenerate)
- Thermonuclear Explosion:
Deflagration/Detonation
- Nickel to Cobalt to Iron Decay +
radiative transfer powers the light
curve

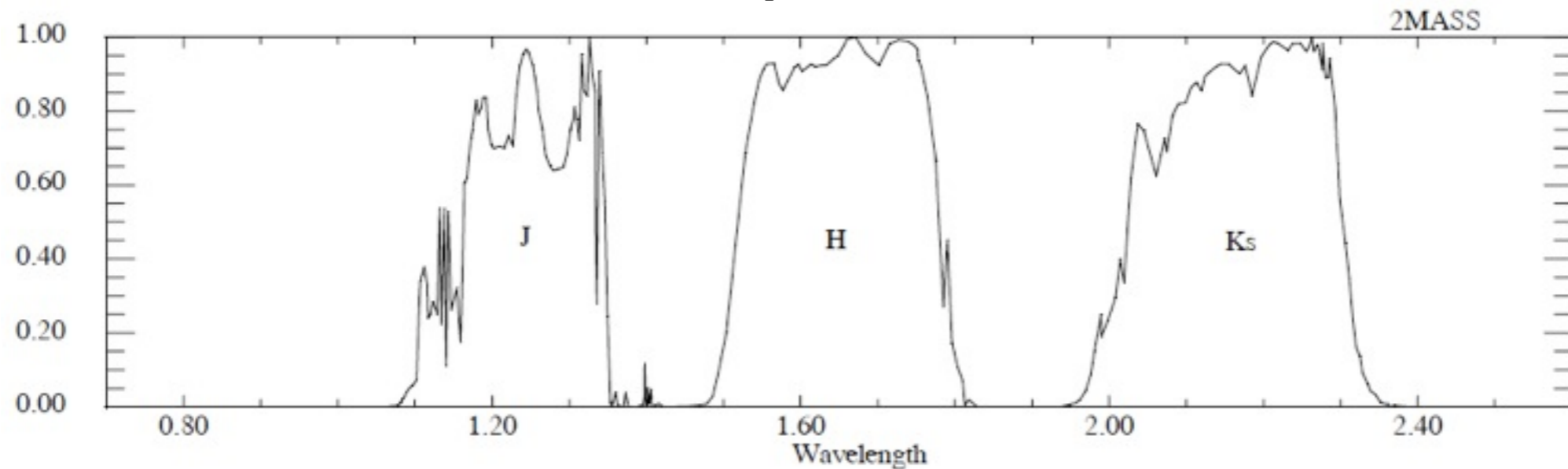


Credit: FLASH Center

Telescopes collect light of different wavelengths

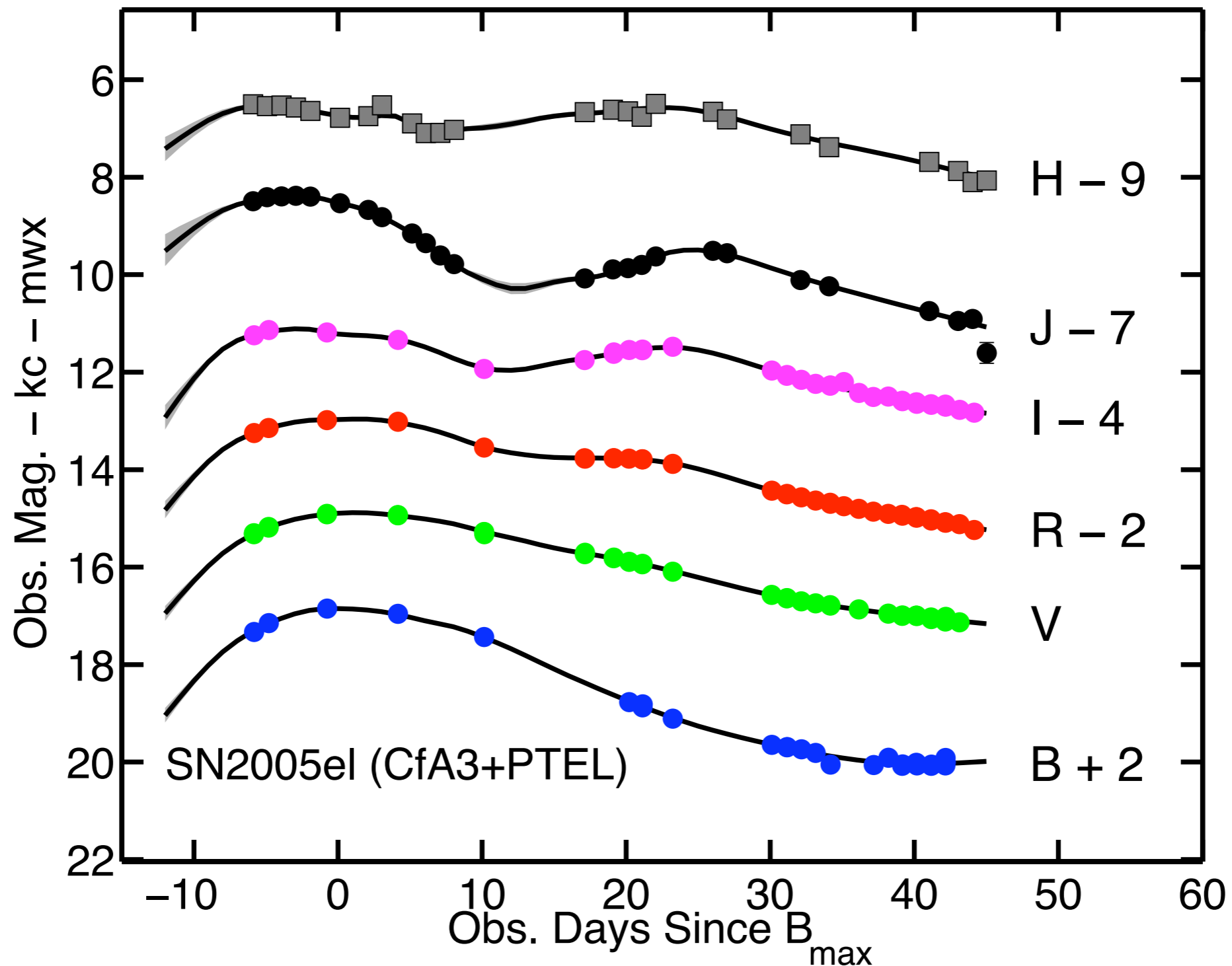


Optical

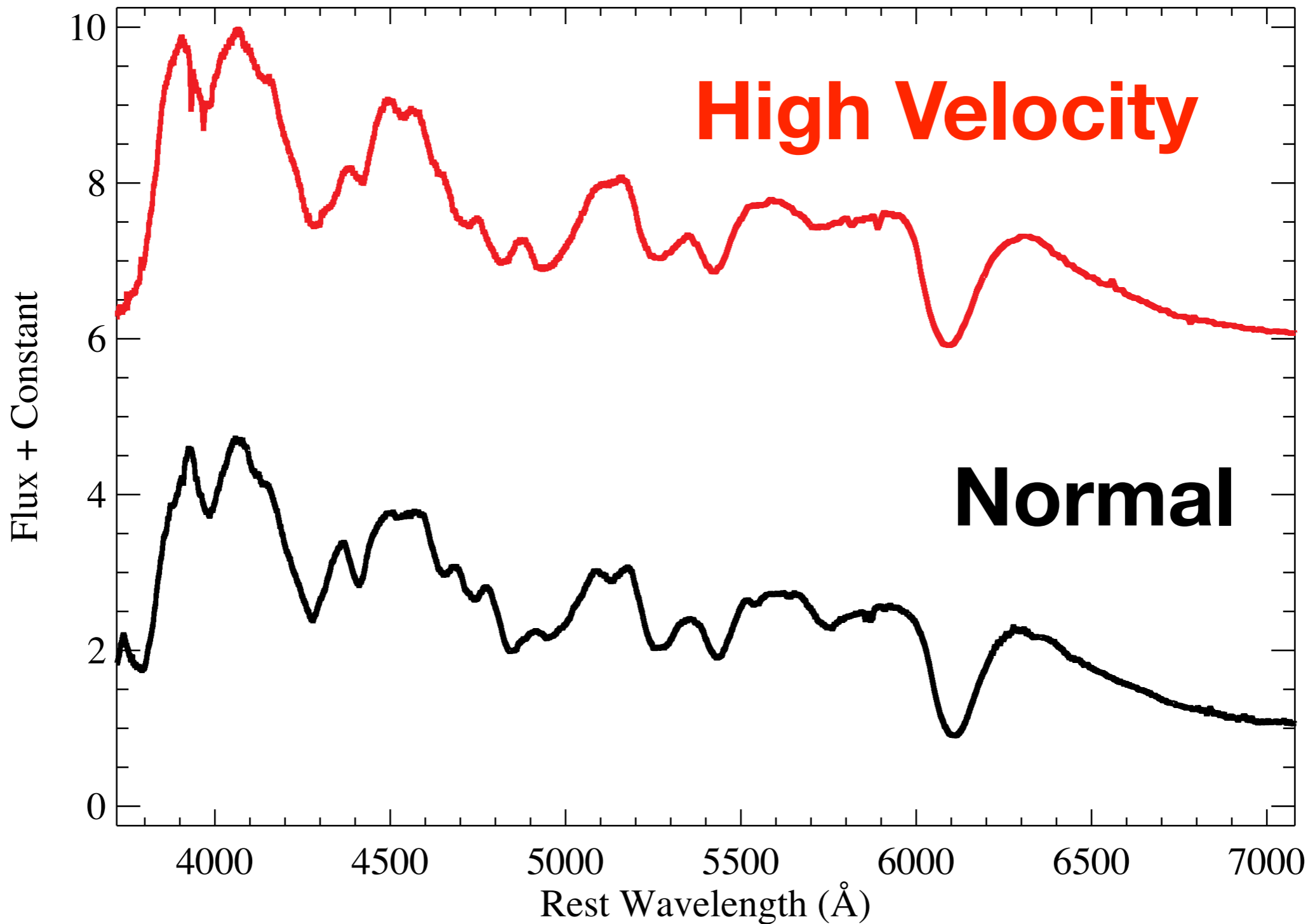


Near Infrared

Observable: Type Ia Supernova Apparent Light Curve (time series)



Observable: Type Ia SN Spectrum



The Accelerating Universe 2011 Nobel Prize in Physics



Distant Type Ia Supernovae

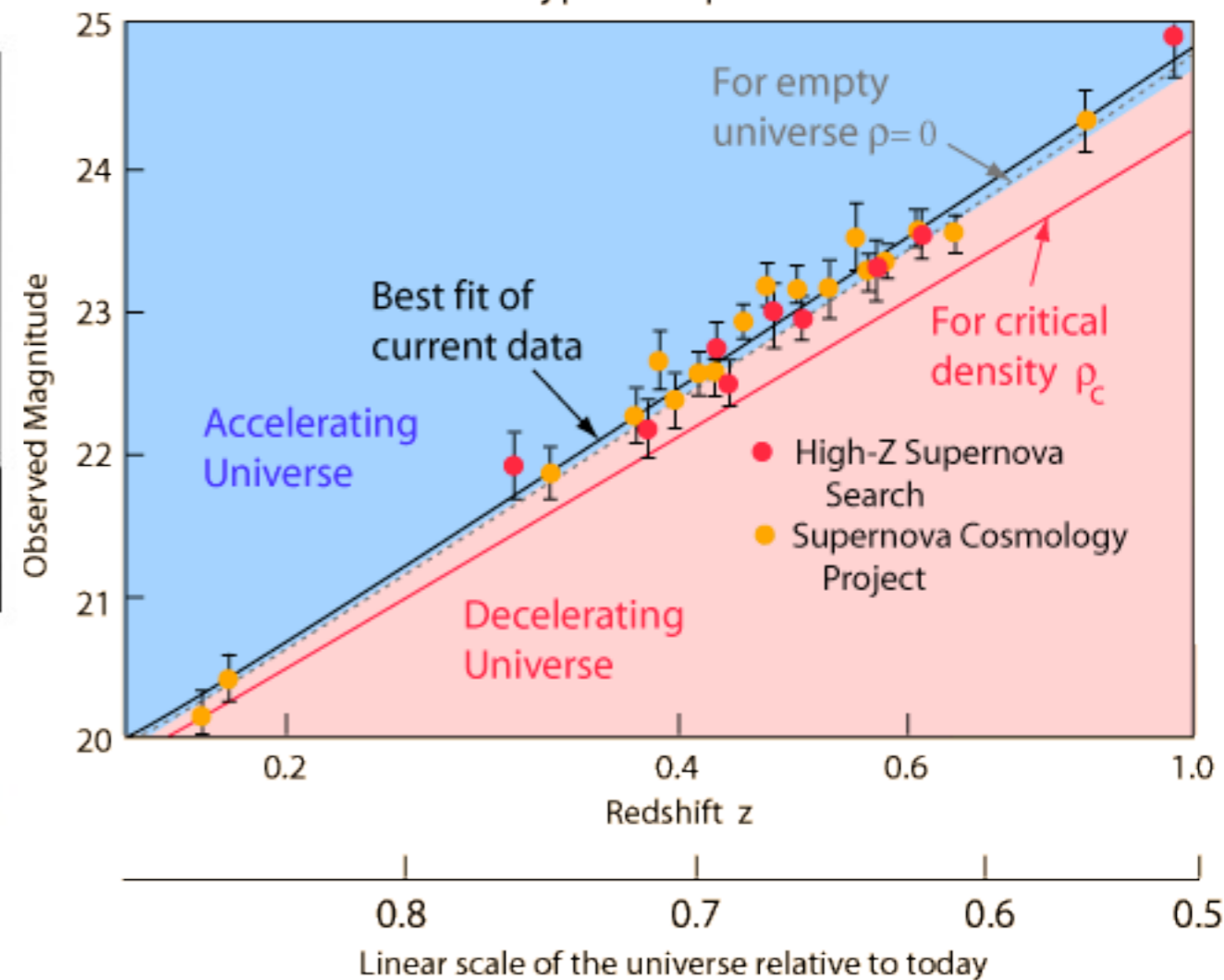


Photo: U. Montan

Saul Perlmutter



Photo: U. Montan

Brian P. Schmidt

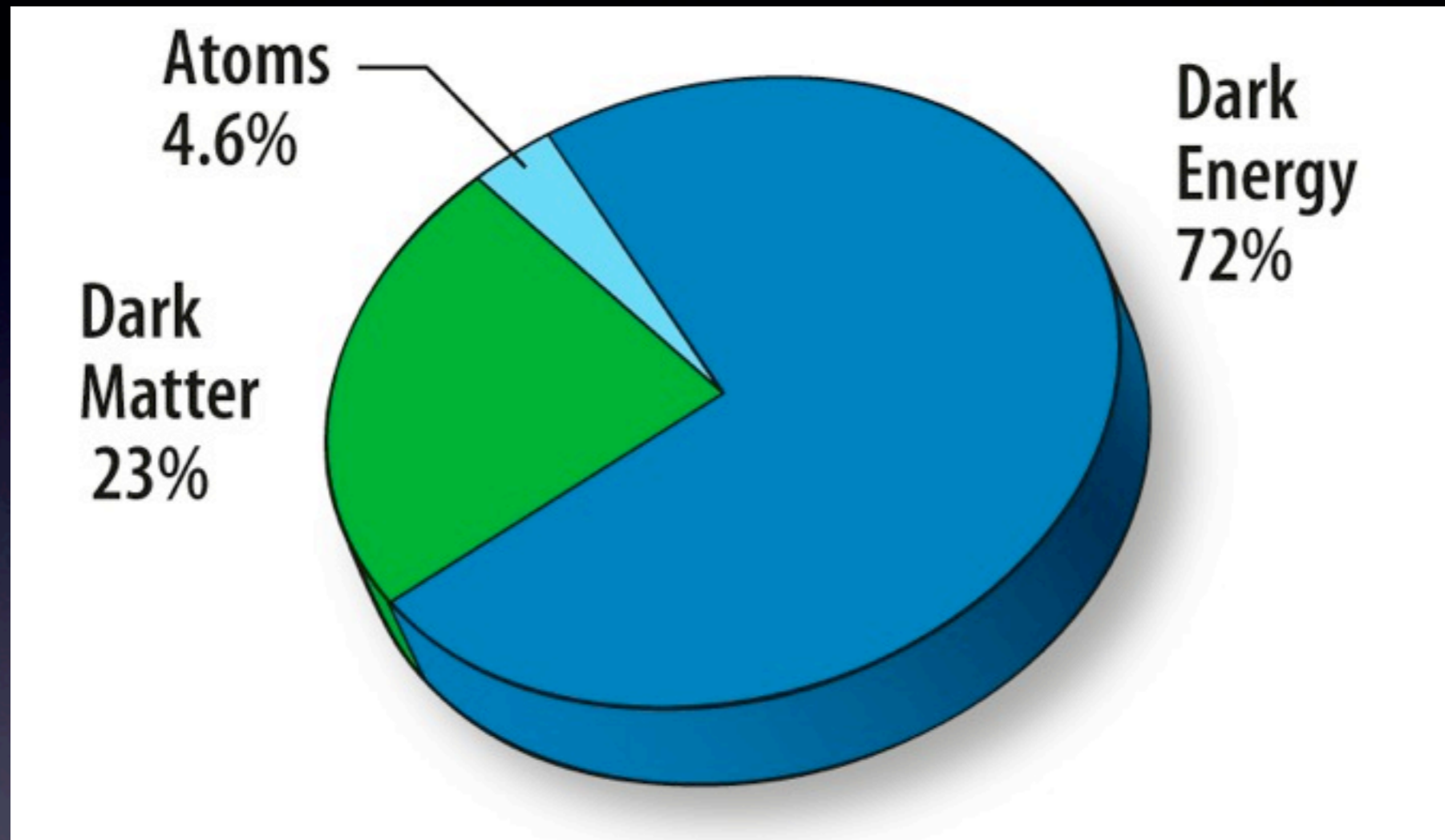


Photo: U. Montan

Adam G. Riess

The Nobel Prize in Physics 2011 was divided, one half awarded to Saul Perlmutter, the other half jointly to Brian P. Schmidt and Adam G. Riess "for the discovery of the accelerating expansion of the Universe through observations of distant supernovae".

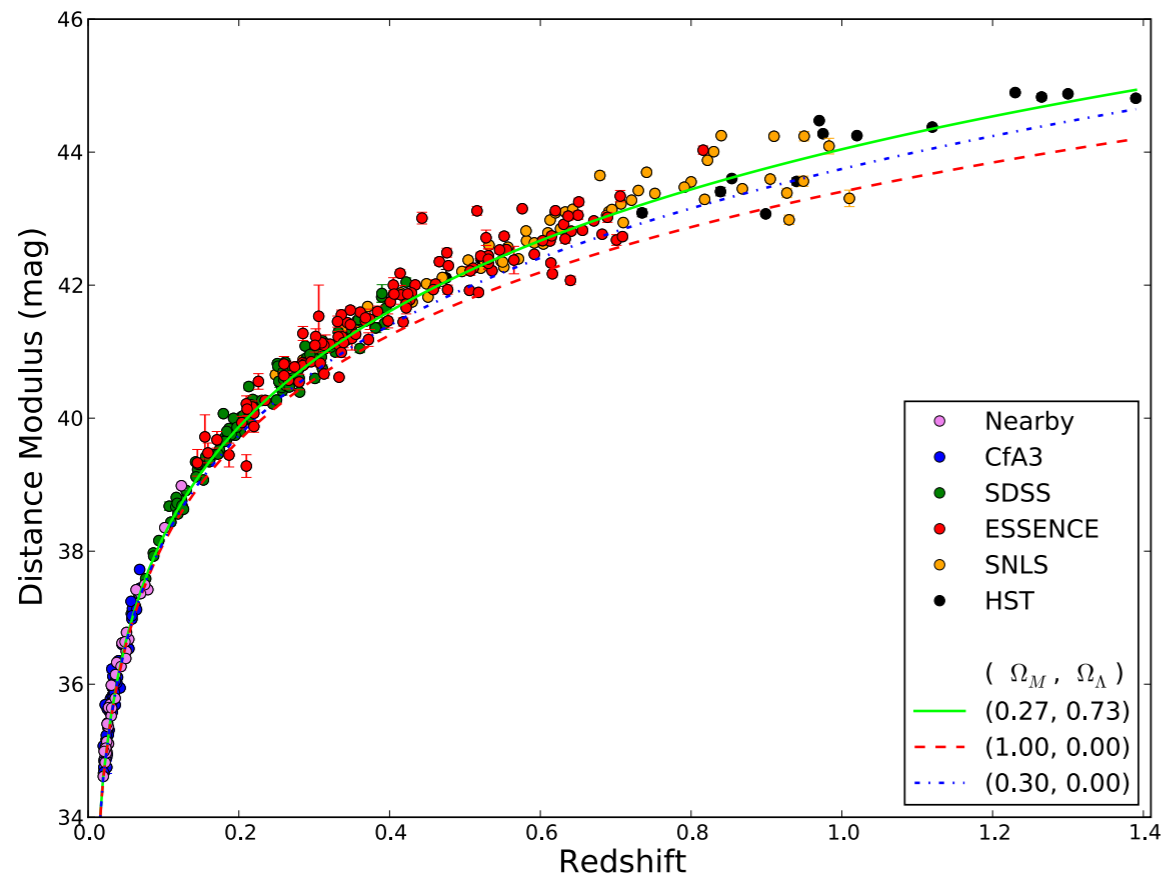
Cosmological Energy Content



Dark Energy Equation of state $P = w\rho$

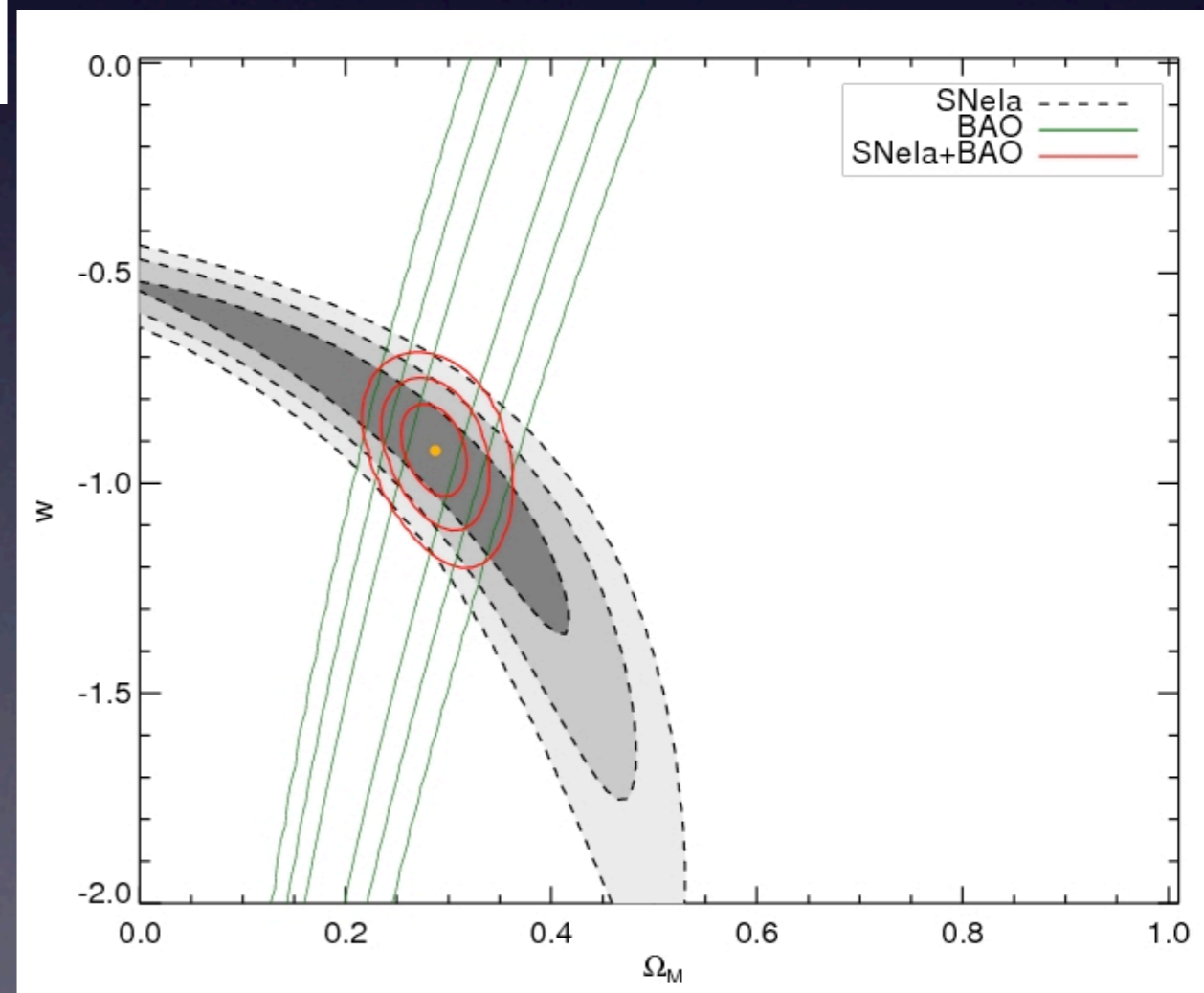
Is $w + 1 = 0$? Cosmological Constant

Supernova Cosmology: Constraining Cosmological Parameters using Luminosity Distance vs. Redshift



Credit: Gautham Narayan
(ESSENCE)

Need accurate distances!
Host Galaxy **Dust** is a
Major Confounding
Factor



Part I:

Supernova Classification

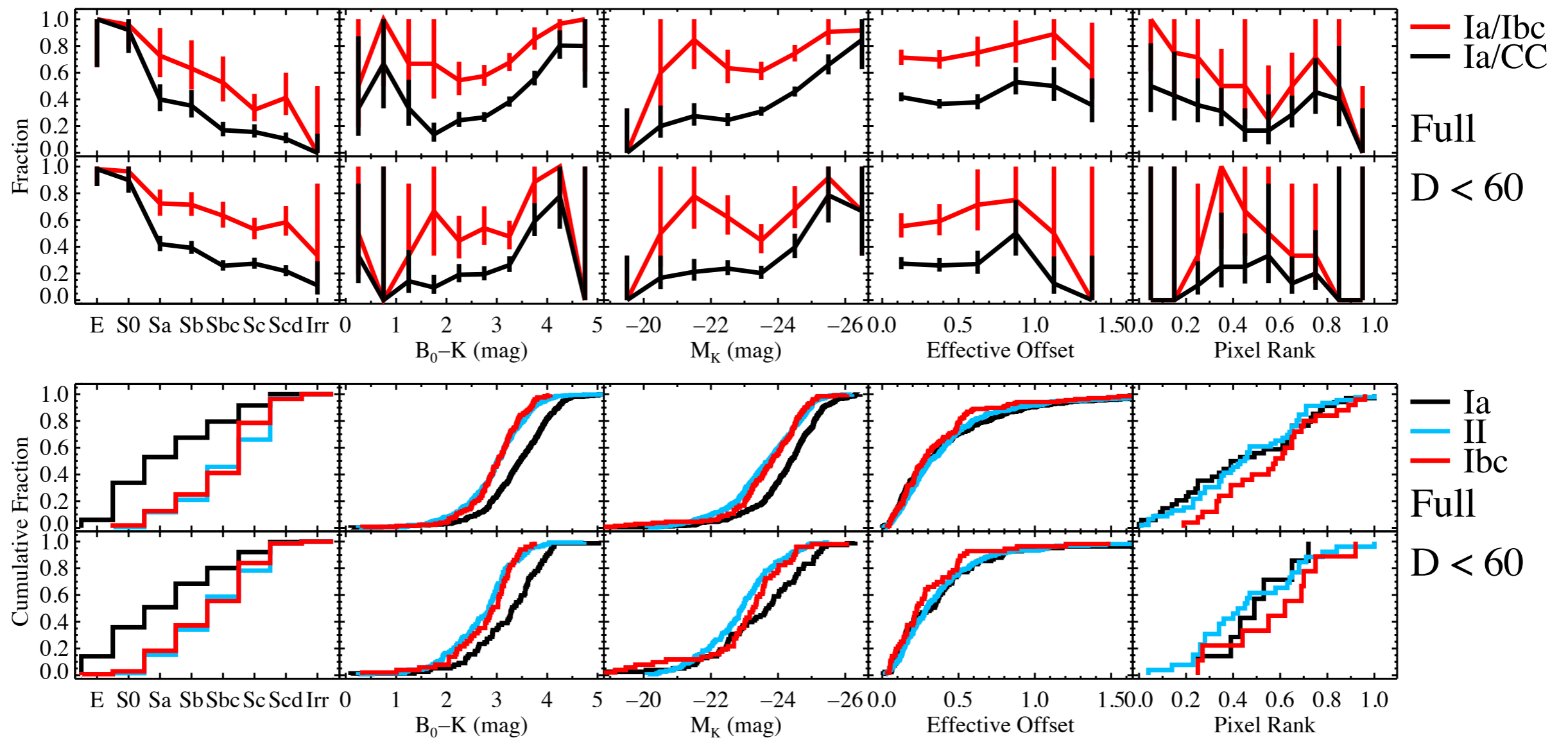
- Core Collapse (CC: II/Ibc) vs. Type Ia (SN Ia)
- Spectroscopic: Obtain spectrum, compare against library of spectrum with known types (SNID)
- For current and future large automated transient surveys (e.g. DES, LSST), too many SN targets, too little telescope time to obtain spectrum for each one
- Photometric: Properties of Broadband light curves

New Alternate Strategy: Use Host Galaxy Properties

(Foley & Mandel 2013, last week!
arxiv.org/abs/1309.2630)

- Use correlations between SN Type and properties of the Host Galaxy (Morph, Color, Luminosity, Position/offset, Pixel brightness rank)
- CC SN rarely occur in red, luminous, early-type galaxies
- CC SN explode in late-type galaxies in spiral arms, SN Ia explode in all types of galaxies
- Uses different data source than traditional typing methods

Distribution of the SN Ia fraction vs. host galaxy property (using LOSS sample)



galsnid: a Naive Bayes Classifier

- Want $P(Ia | \mathbf{D}) \propto P(\mathbf{D} | Ia) P(Ia)$
- Modeling $P(\mathbf{D} | Ia)$ is hard for multidimensional \mathbf{D}
- Simplify by assuming D_i are conditionally independent given the class

- $$P(\mathbf{D} | Ia) = \prod_{i=1}^n P(D_i | Ia)$$

- **galsnid probability**
$$P(Ia | \mathbf{D}) \propto P(Ia) \prod_{i=1}^n P(D_i | Ia)$$

Application to LOSS training set

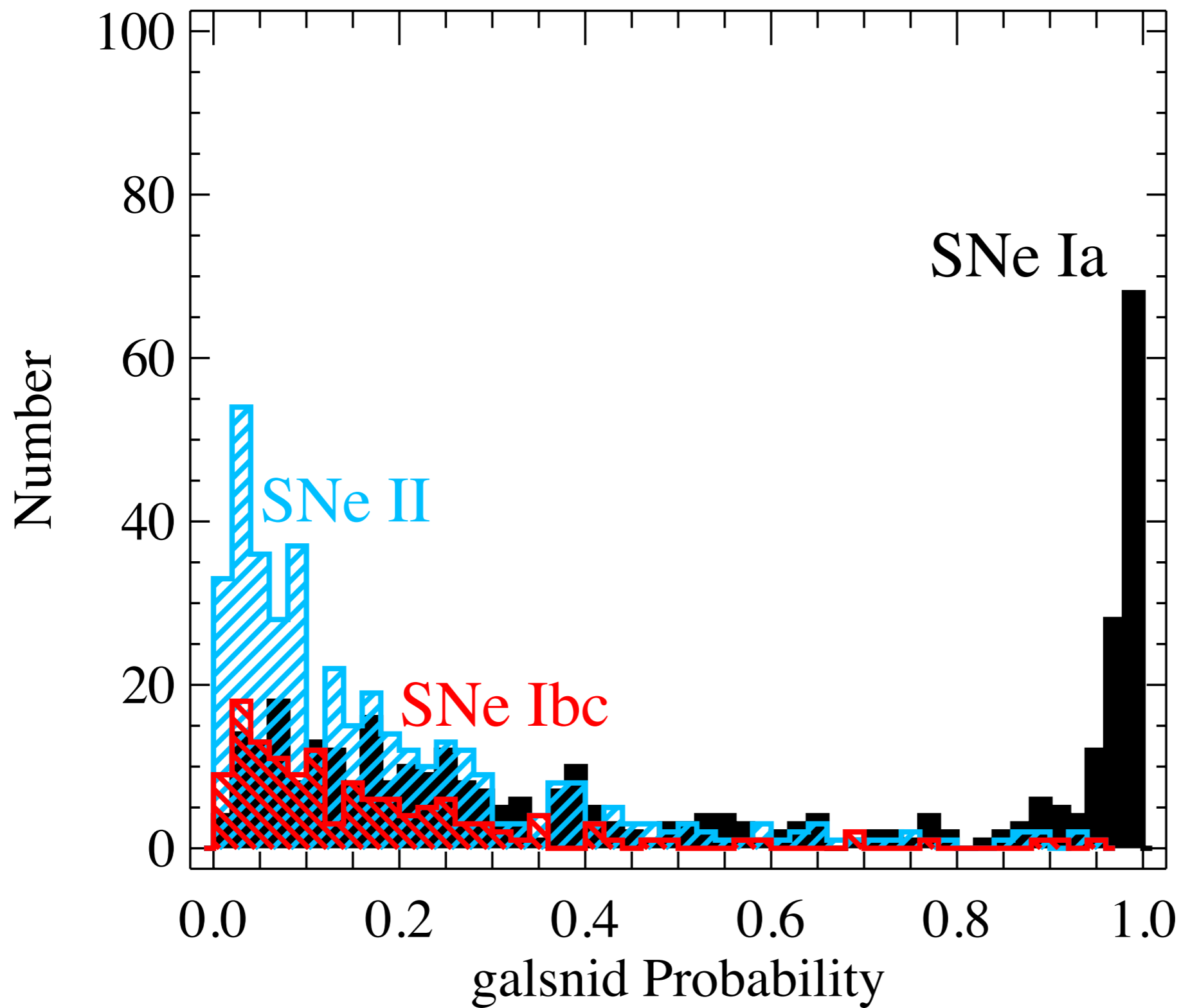


Figure of Merit

- Choose a subset with galsnid $p >$ threshold p^*
- FoM = Efficiency x Pseudopurity
- Efficiency $\epsilon_{Ia} = N_{Ia}^{Sub} / N_{Ia}^{Tot}$
- Pseudopurity $PP_{Ia} = \frac{N_{Ia}^{Sub}}{N_{Ia}^{Sub} + W_{Ia}^{False} N_{Non-Ia}^{Sub}}$
- $W = 5$, penalizes misclassified SN Ia

FoM as function of threshold *galsnid* p

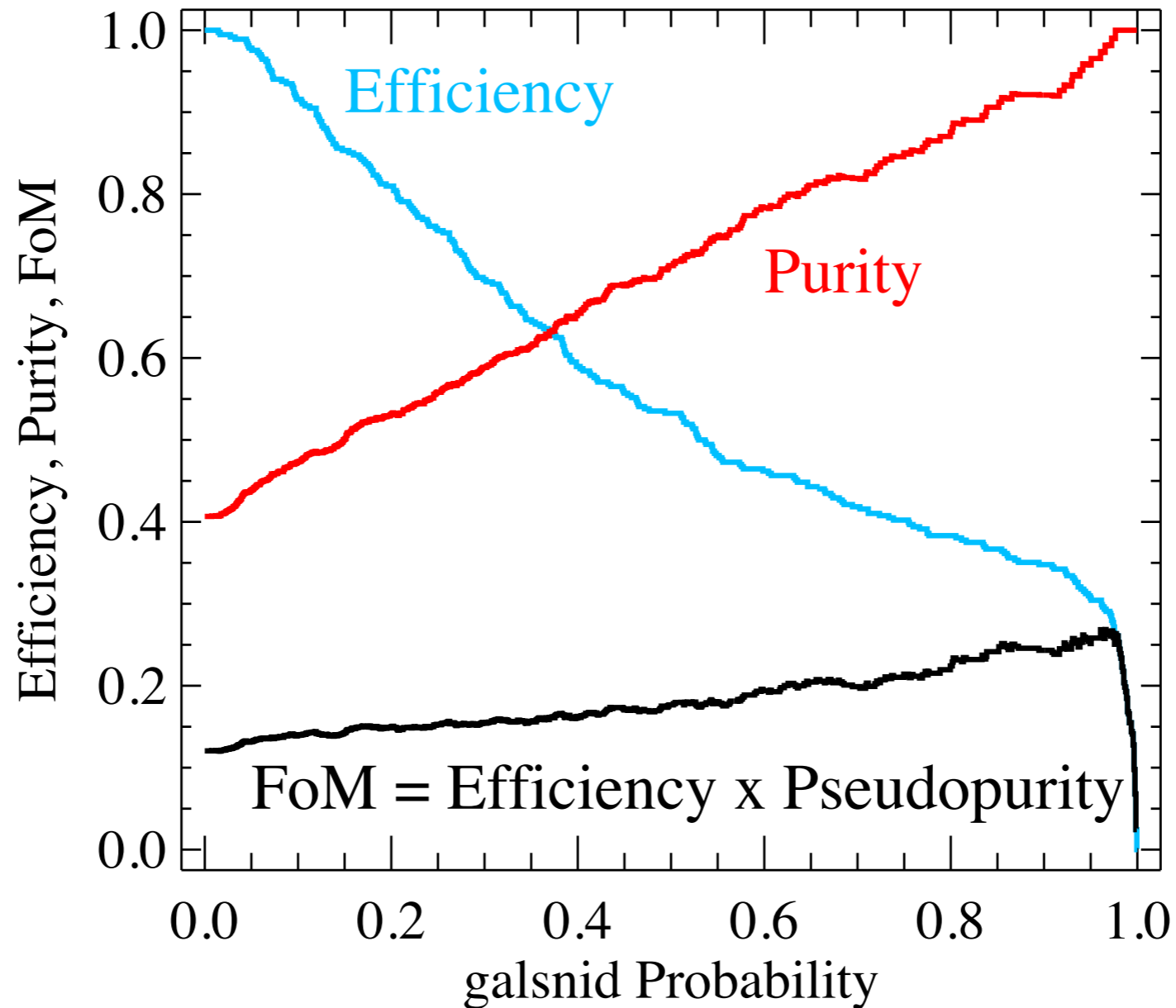


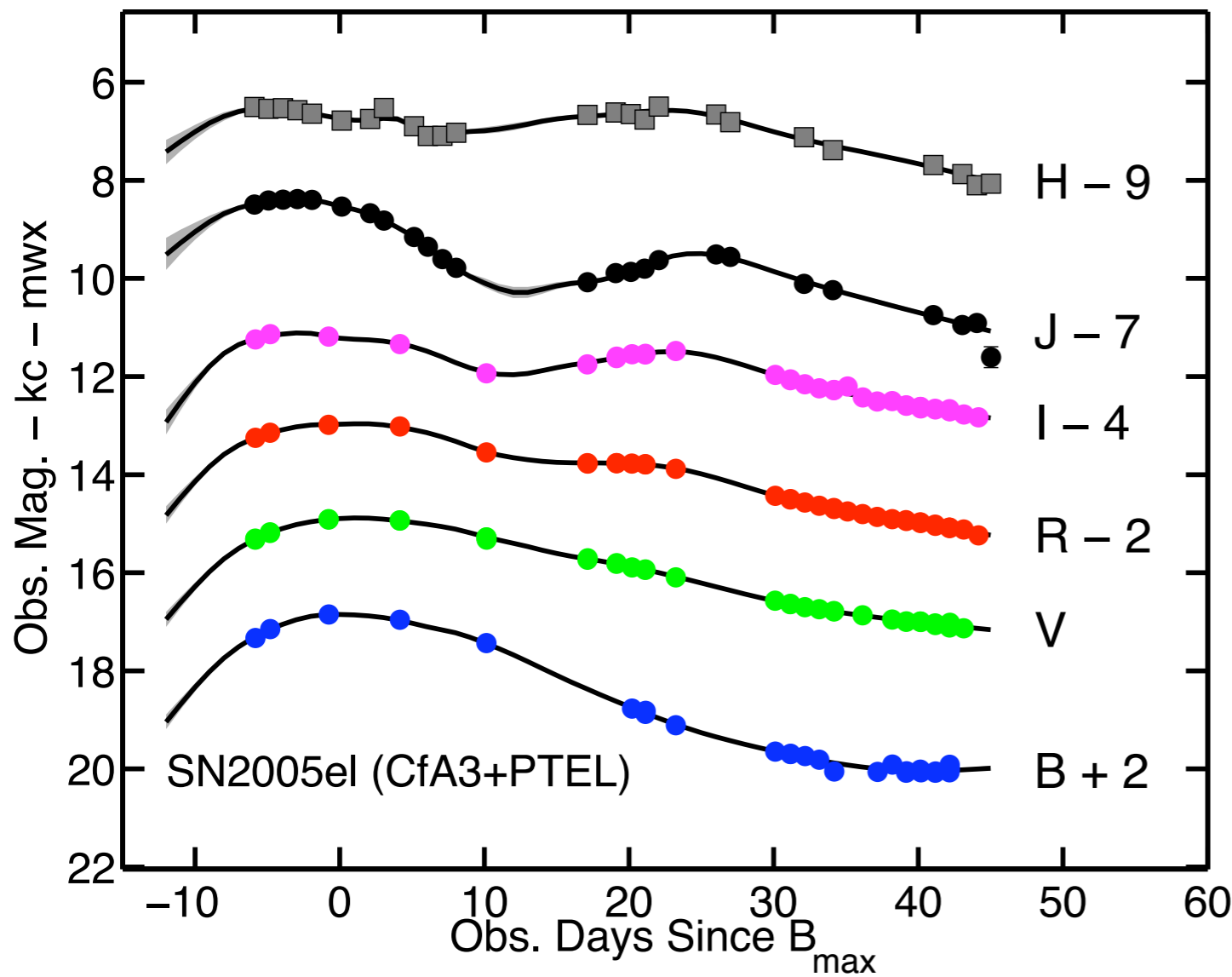
FIG. 3.— Efficiency, purity, and FoM (blue, red, and black curves, respectively) for subsamples of the LOSS sample defined by a particular *galsnid* probability or larger. The FoM peaks at $p = 0.97$ at a value that is 2.23 times larger than the FoM for the entire sample.

galsnid evaluation

- Max FoM is 2.23x improvement over baseline
- Comparable to photometric light curve method (2.6x)
- 2-fold Cross-Validation (split into two samples, alternate training and test sets)
- CV FoM = 1.4 (even training), 2.4 (odd training)
- Also test on independent SN samples (SDSS, PTF)
- galsnid: an effective and independent SN classifier

Part II: Hierarchical Bayesian Regression

Model for SN Ia Colors and Spectroscopic Velocities



Astronomer's Definition:

Color = Numerical
difference in brightness
magnitude in two
passbands

e.g. B - V Color

More Positive = "Redder"
More Negative = "Bluer"

Observed Color = Intrinsic Color + Dust Reddening
+ Measurement Error

I will show you fear in a handful of dust

Dust Absorption vs. Wavelength of Light

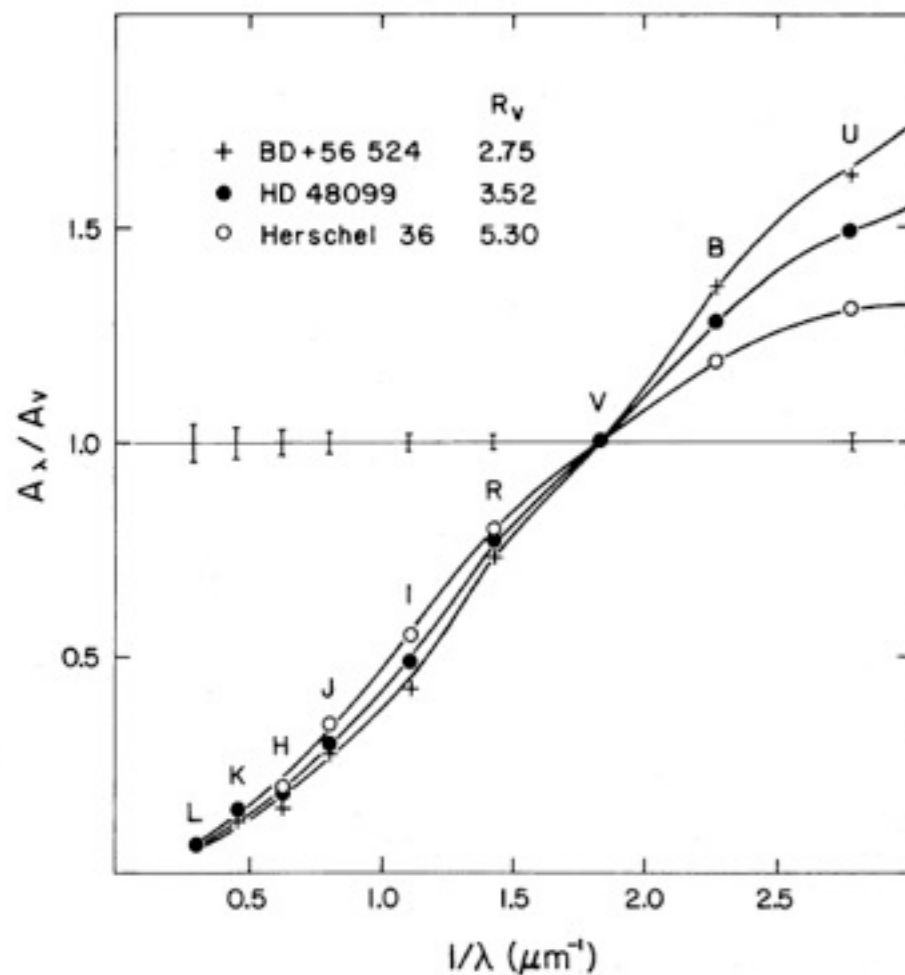
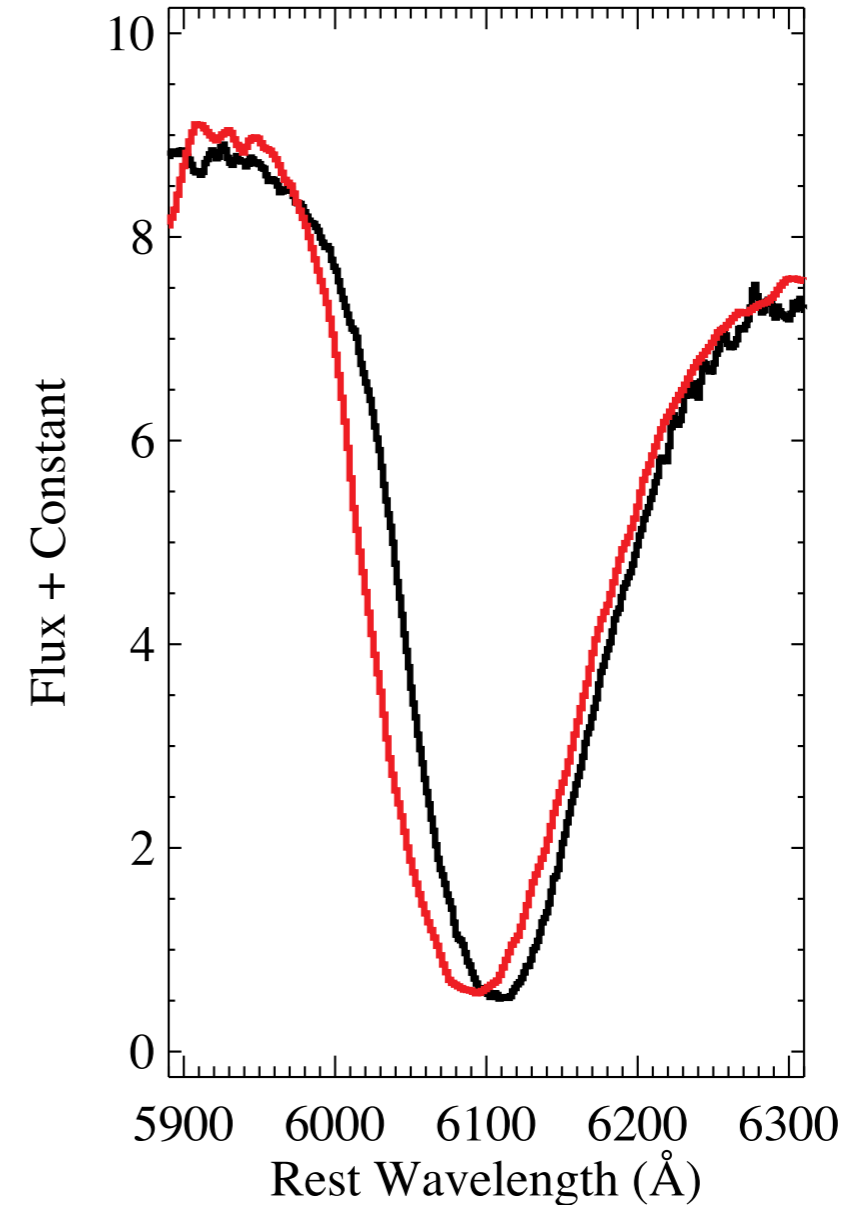
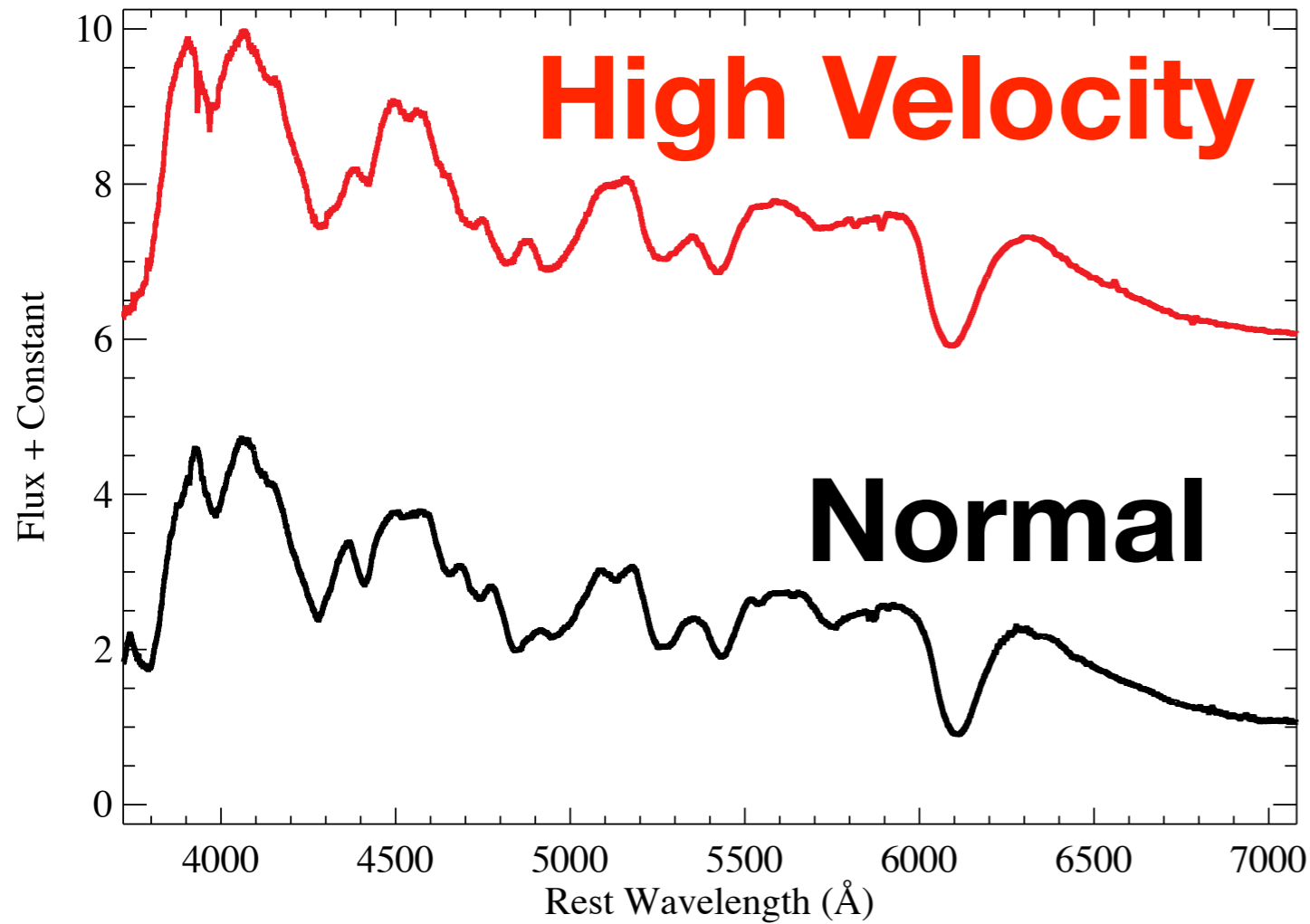


FIG. 3.—Comparison between the mean optical/NIR R_V -dependent extinction law from eqs. (2) and (3) and three lines of sight with largely separated R_V values. The wavelength position of the various broad-band filters from which the data were obtained are labeled (see Table 3). The “error” bars represent the computed standard deviation of the data about the best fit of $A(\lambda)/A(V)$ vs. R_V^{-1} with $a(x) + b(x)/R_V$ where $x \equiv \lambda^{-1}$. The effect of varying R_V on the shape of the extinction curves is quite apparent, particularly at the shorter wavelengths.

- Absorption depends on λ (reddening)
- Interstellar lines of sight to SN in different galaxies can pass through different random amounts of dust
- Key Parameters of Interstellar Dust (different for each SN)
 - $A_V \sim$ Amount of Dust Absorption (only positive!)
 - $R_V \sim$ Wavelength Dependence of Dust Absorption
- Don't really know a priori which SN are unaffected by dust; must model probabilistically

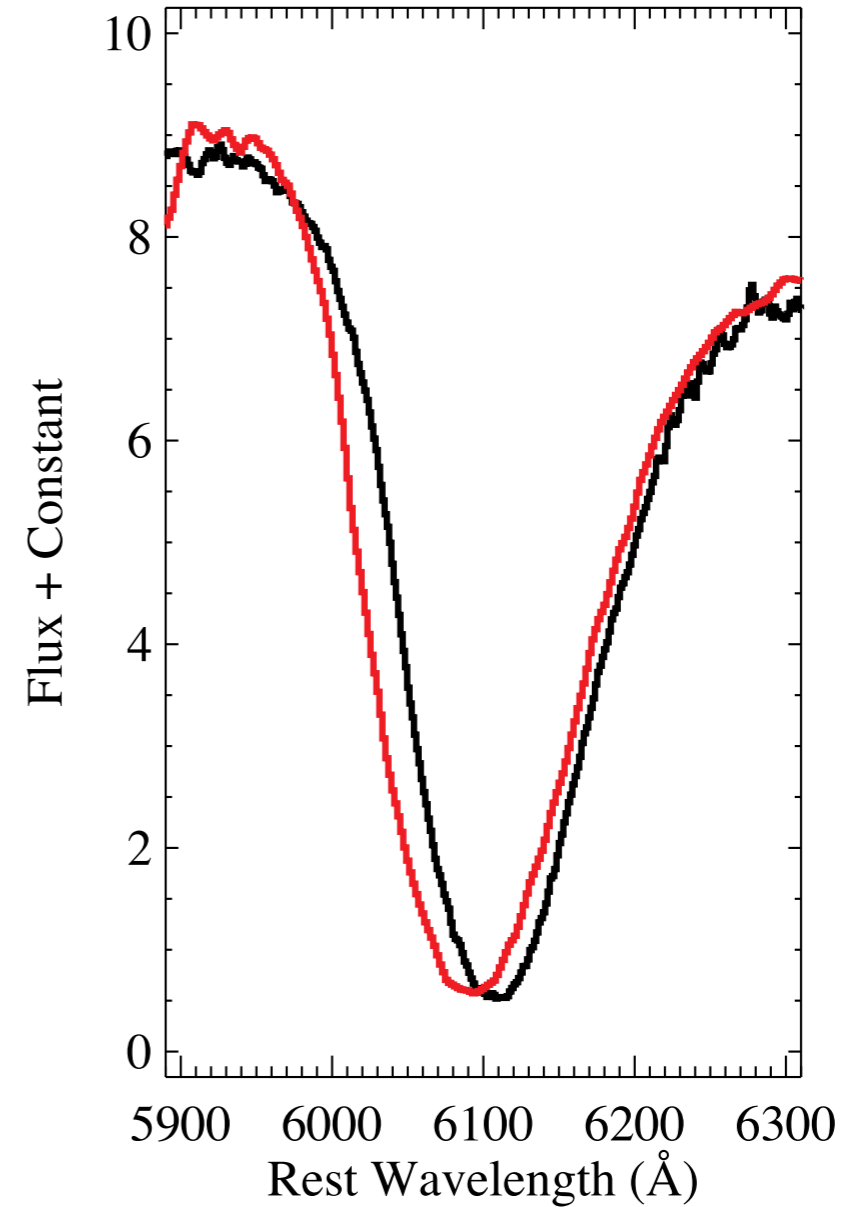
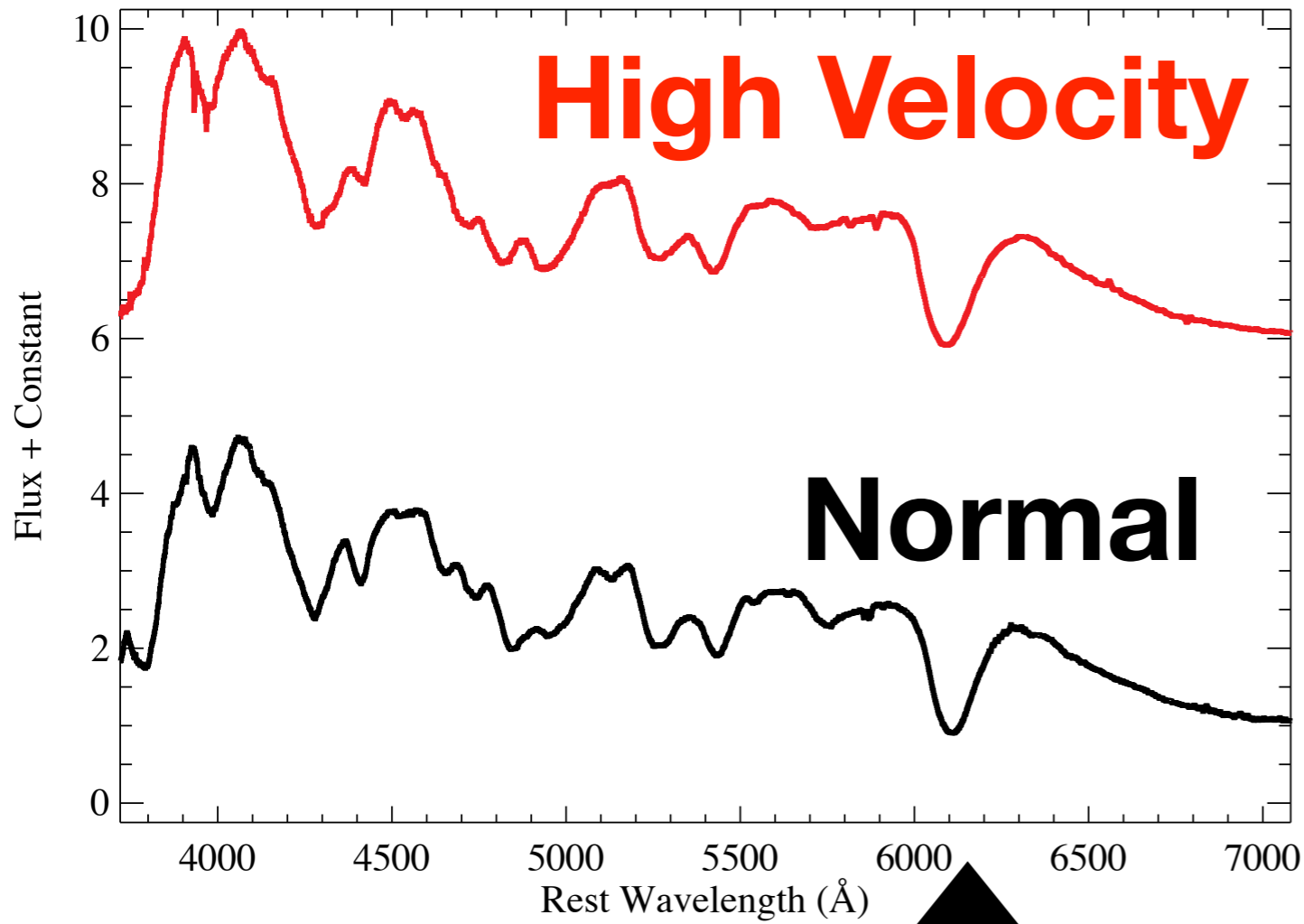
Si II $\lambda 6355$ line



Ryan Foley,
Stephane Blondin

Foley & Kasen 2011 :
Velocity Related to
Line opacity in B

Si II $\lambda 6355$ line



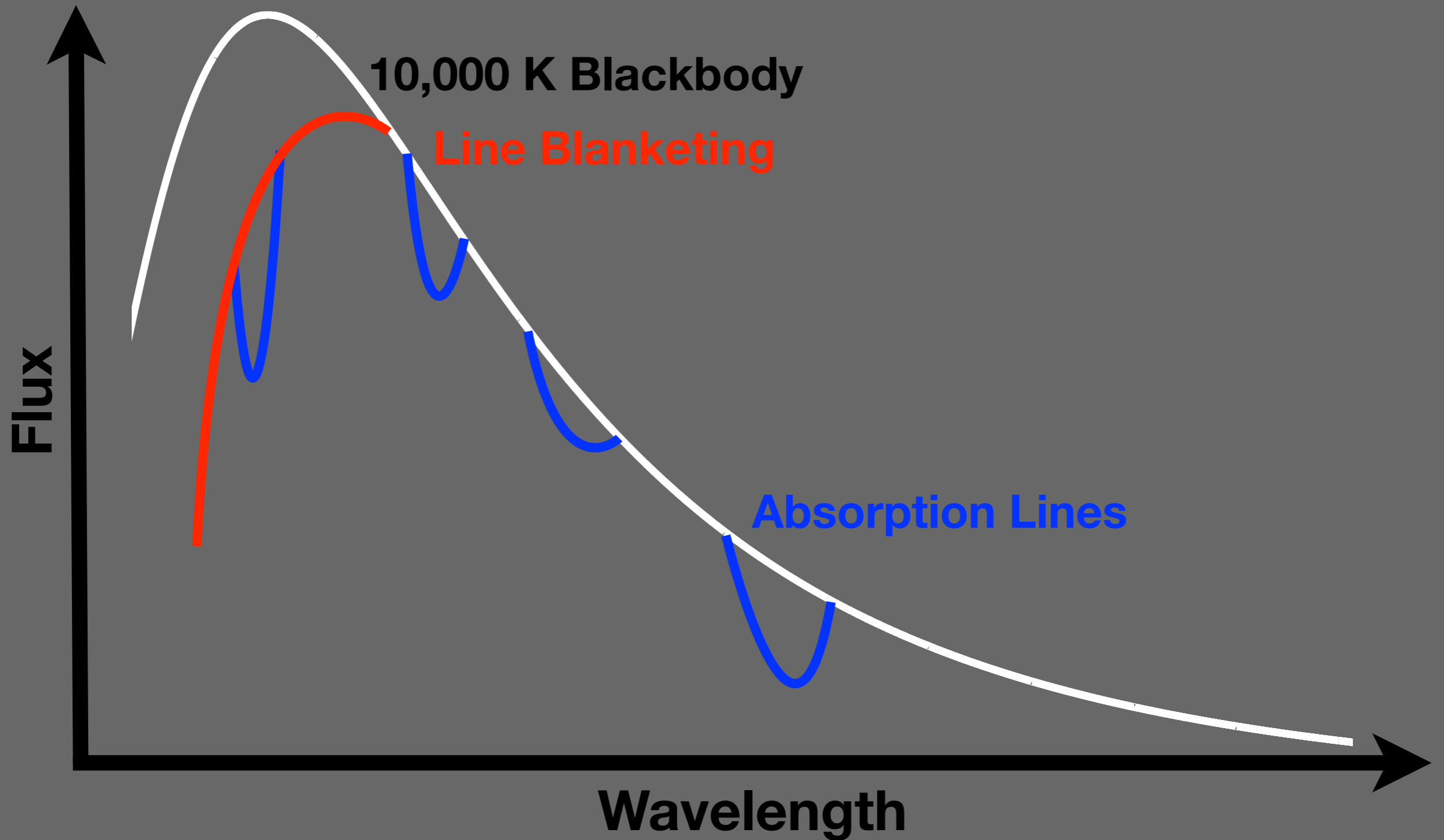
Ryan Foley,
Stephane Blondin **Silicon**

Foley & Kasen 2011 :
Velocity Related to
Line opacity in B

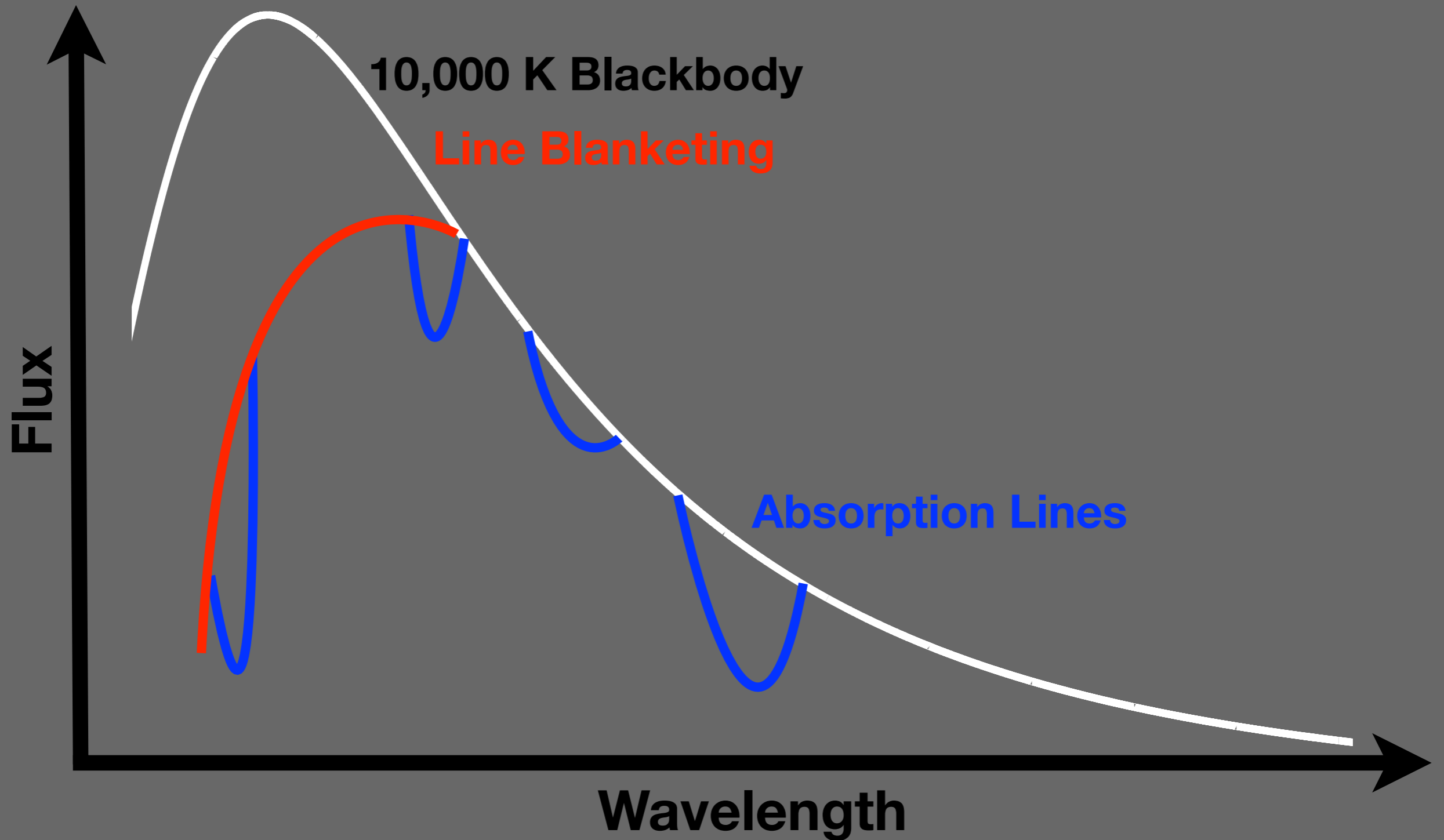
SN Ia Ejecta Velocities and Optical Colors

- Foley & Kasen (2011): Si II velocity is correlated with Peak Intrinsic B-V color
- High Ejecta Velocity : Broader Absorption Lines in B-band : Redder SN color
- Velocity can help determine intrinsic color, improve SN Ia dust and distance estimates

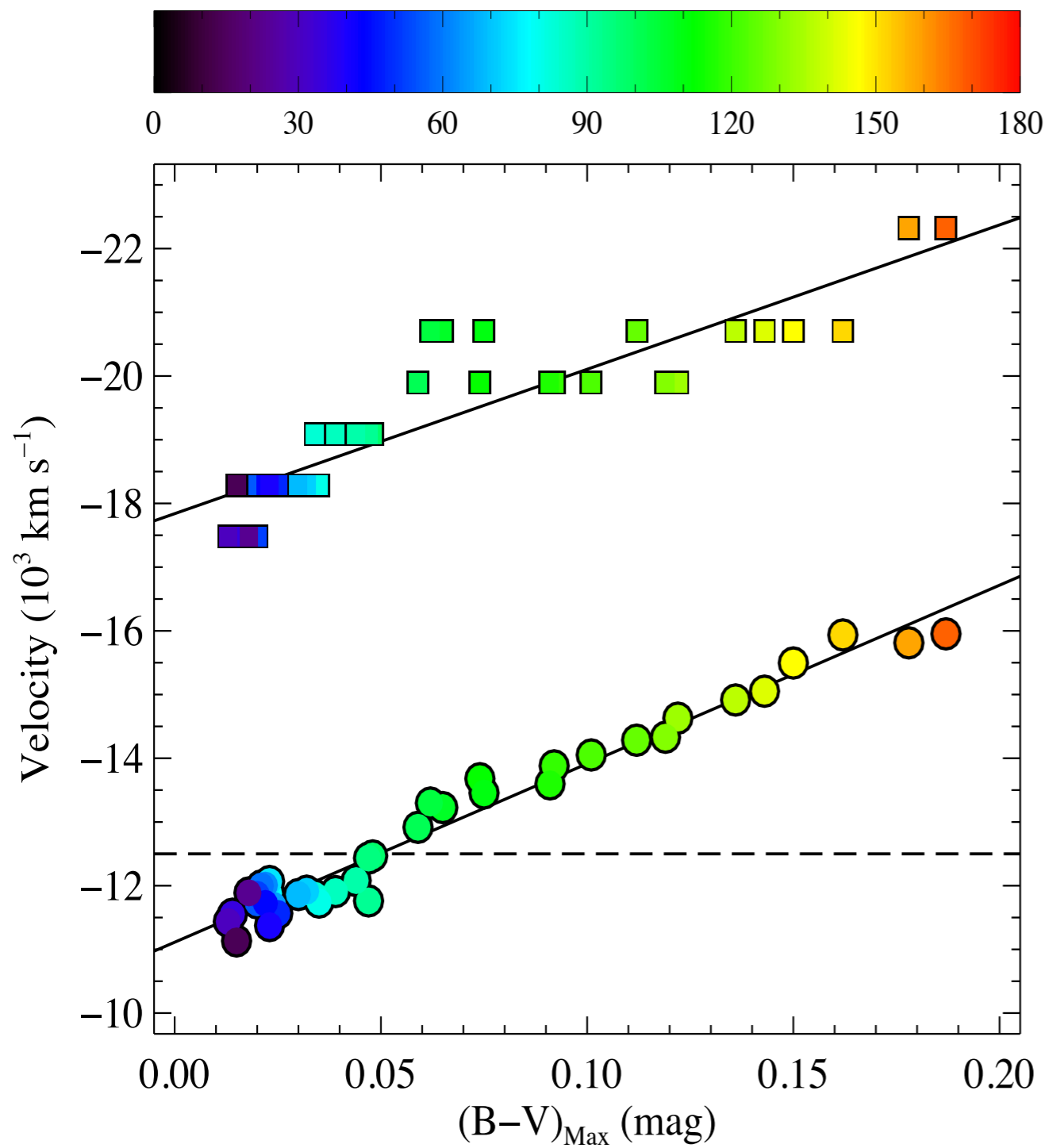
Supernova SED Toy Model



Supernova SED Toy Model



Theoretical Model



- Asymmetric SN Ia Explosion Model
- Predicts Linear relation between intrinsic color and velocity

Foley & Kasen 2011

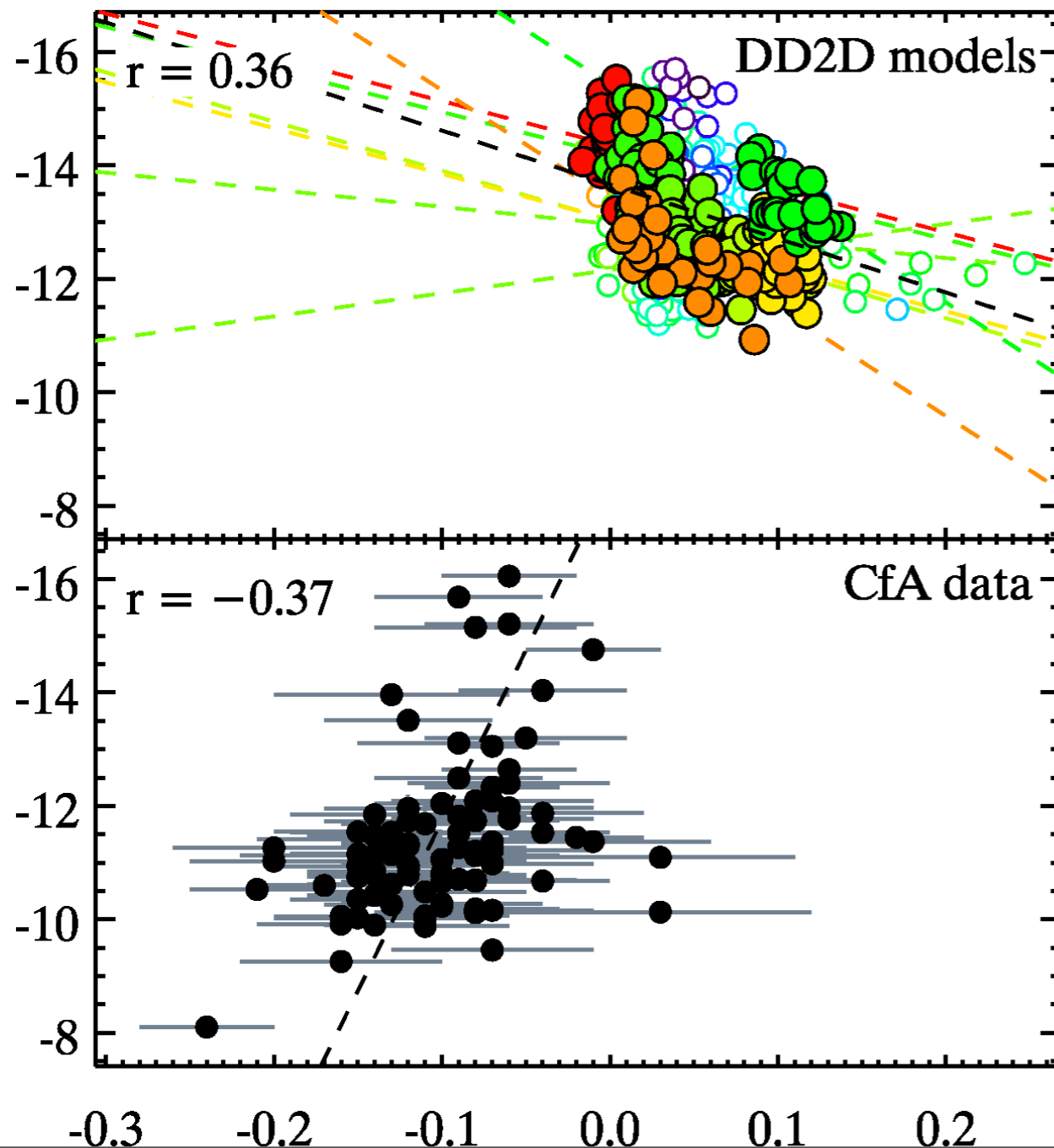
Testing Theoretical Explosion Models

Blondin, Kasen, Röpke, Kirshner & Mandel. 2011

mean rlap averaged over all viewing angles



5.1 5.9 6.7 7.5 8.3 9.1 9.9



Other models do not show a clear relation between Si II velocity vs Intrinsic B-V color

Want to estimate trend from the data

Estimating the Population Intrinsic Color-Velocity Relation

- C = Intrinsic Color, O = Observed Color
- If have measurements (C, v) for each individual SN, then just regress C against v
- But we measure (O, v) where $O = C + \text{Dust Reddening} + \text{Error}$
- How do we estimate population relation between C vs v using (O, v) as data?

What is Hierarchical Bayes?

Simple Bayes: $\mathcal{D} | \theta \sim \text{Model}(\theta) + \epsilon$

Posterior: $P(\theta | \mathcal{D}) \propto P(\mathcal{D} | \theta)P(\theta)$

Hierarchical Bayes: $\theta_i = \text{Individual}$
 $\alpha, \beta = \text{Group or Population}$

$\mathcal{D}_i | \theta_i \sim \text{Model}(\theta_i) + \epsilon$

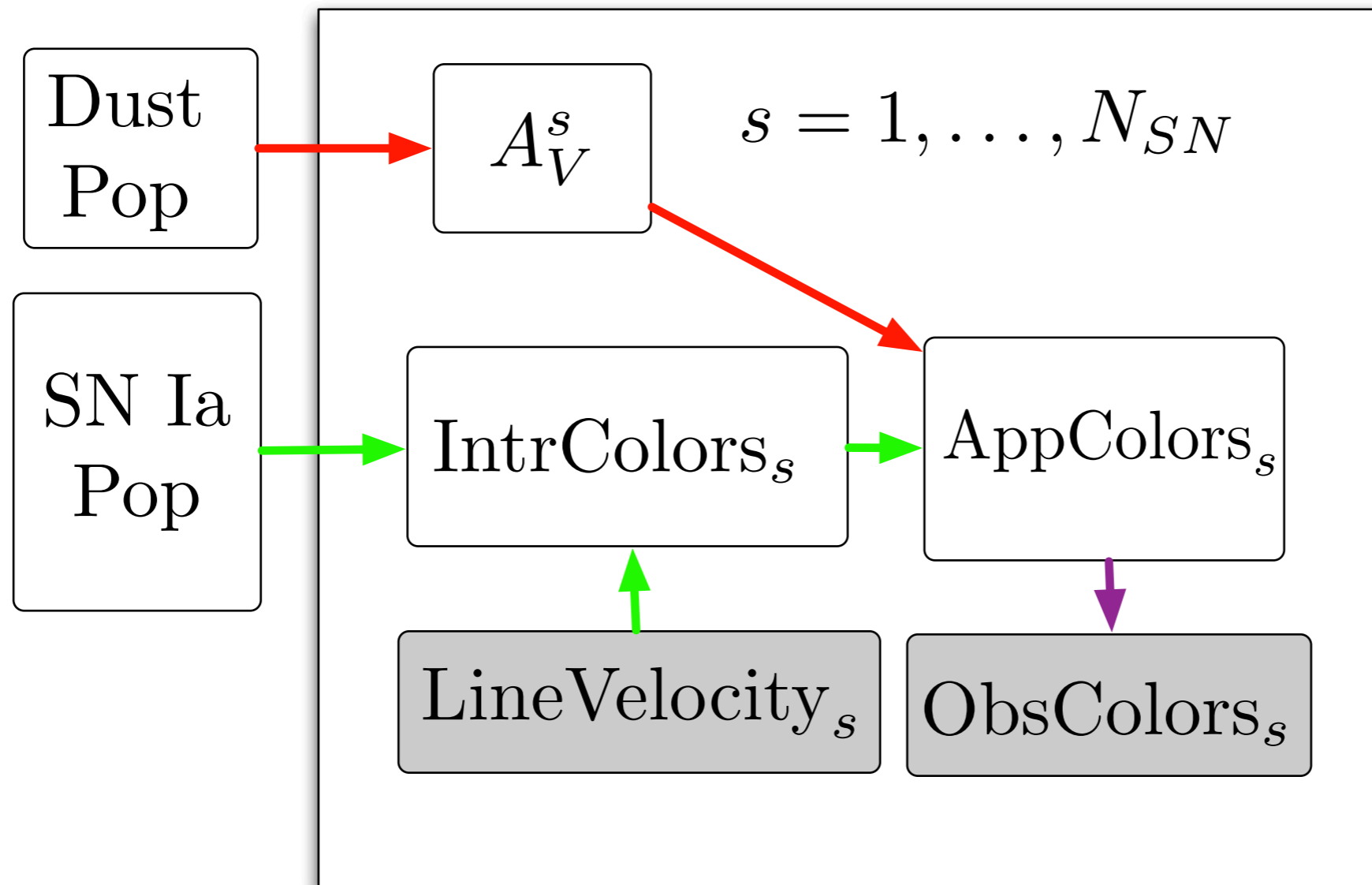
$\theta_i | \alpha, \beta \sim P(\theta | \alpha, \beta)$

Joint Posterior:

$$P(\{\theta_i\}, \alpha, \beta | \{\mathcal{D}_i\}) \propto \left[\prod_{i=1}^N P(\mathcal{D}_i | \theta_i) P(\theta_i | \alpha, \beta) \right] P(\alpha, \beta)$$

Build up complexity by layering conditional probabilities

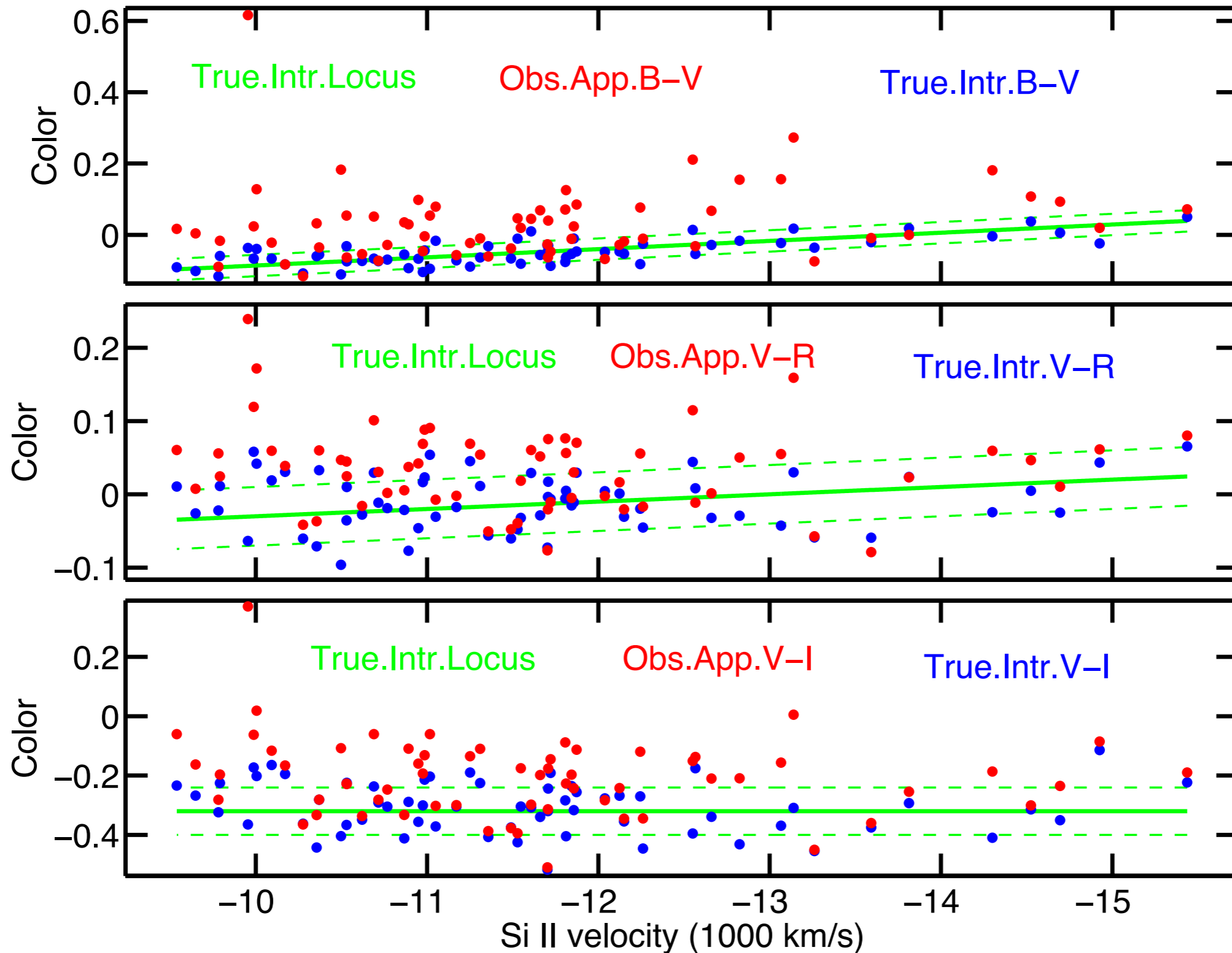
Graphical Model for Color-Velocity Hierarchical Model



Mathematical Details

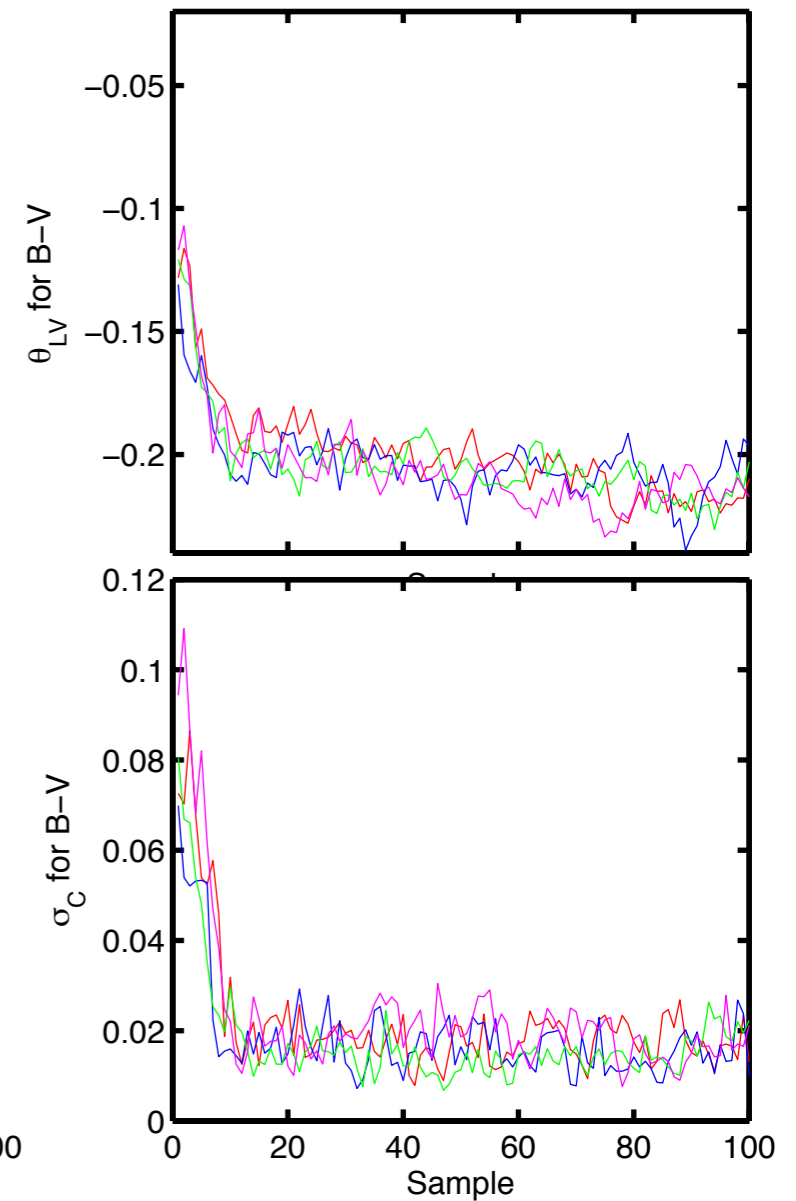
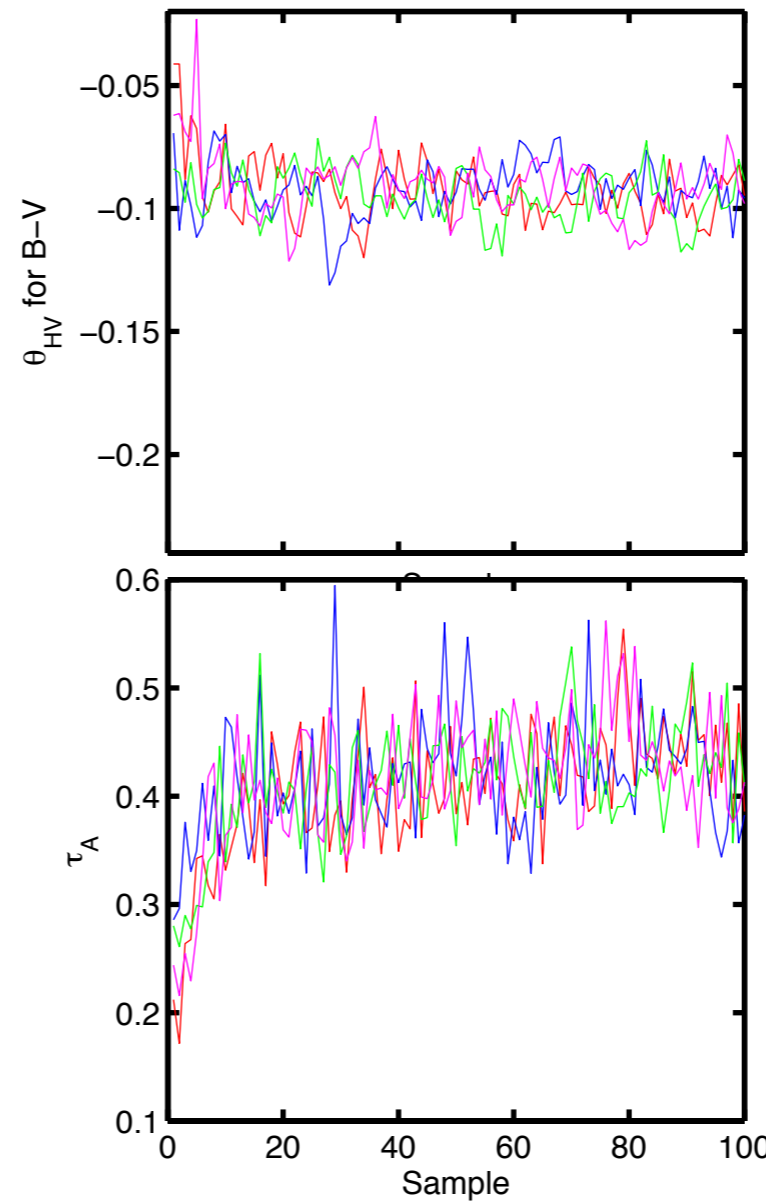
- Pick a form for population mean intrinsic color-velocity function: $\mu_C(v_s; \theta)$
- Individual Intrinsic Colors: $C_s = \mu_C(v_s; \theta) + \epsilon_s^C$.
- Observed Colors: $O_s = C_s + A_V^s \gamma(R_V) + \epsilon_s$.
- Dust Distribution: $A_V^s \sim \text{Expon}(\tau_A)$

Simulated Data from Hierarchical Model

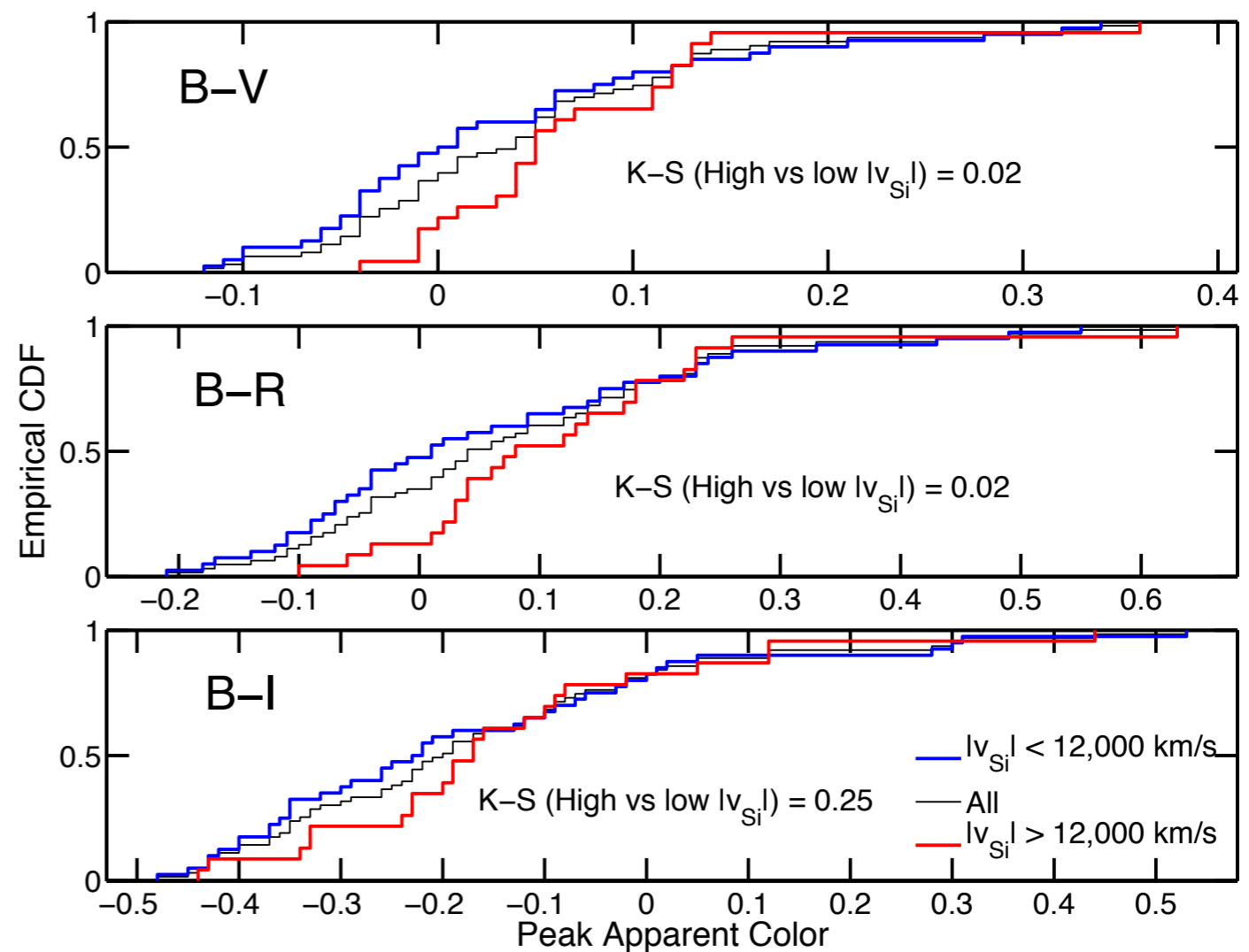
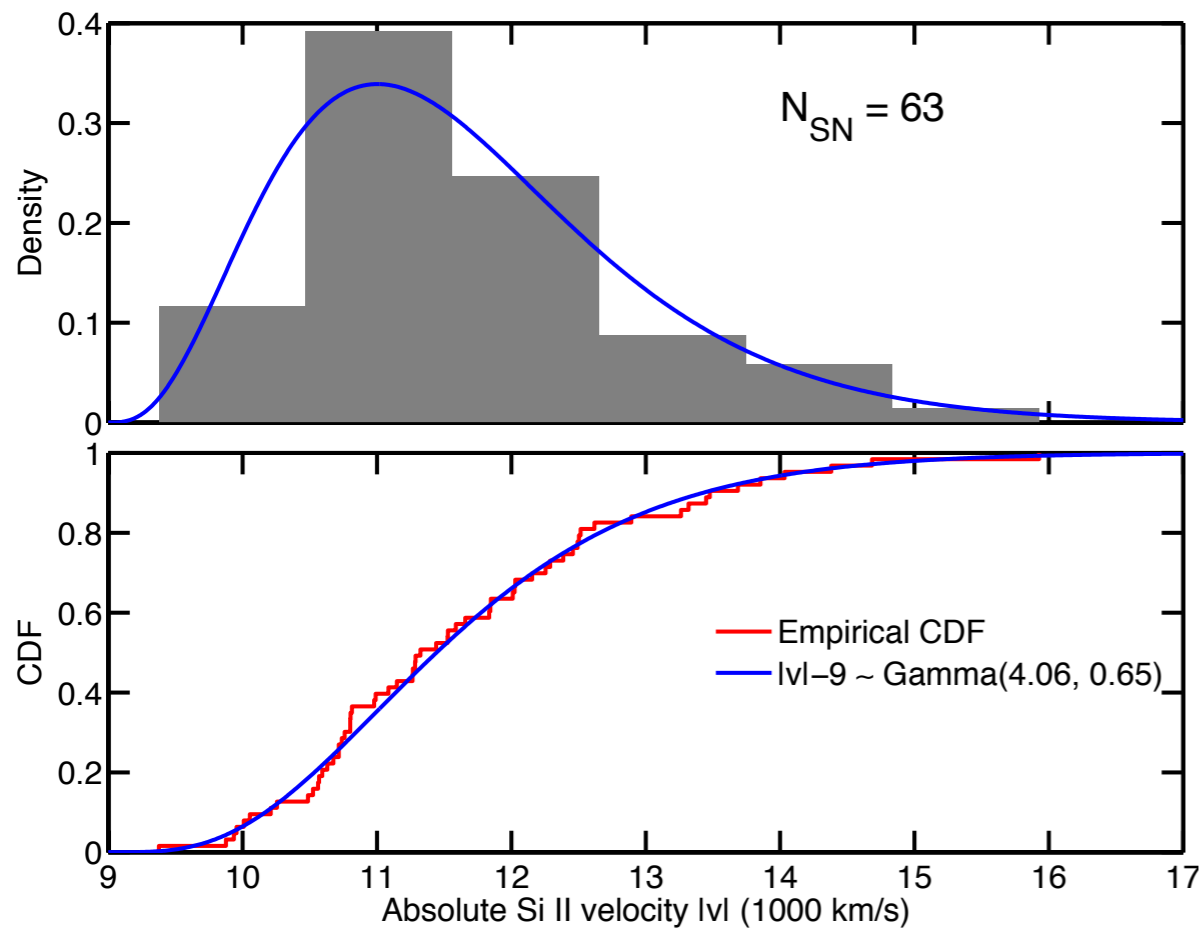


Gibbs Sampling the Posterior Distribution

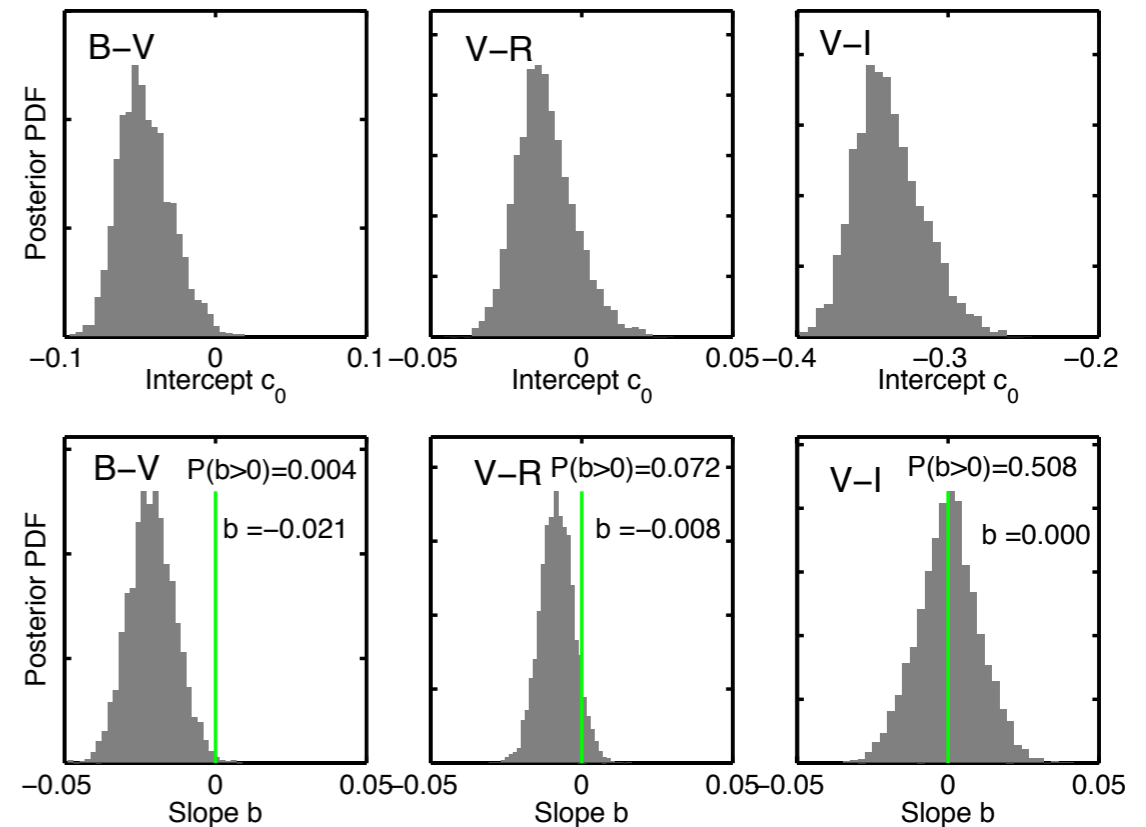
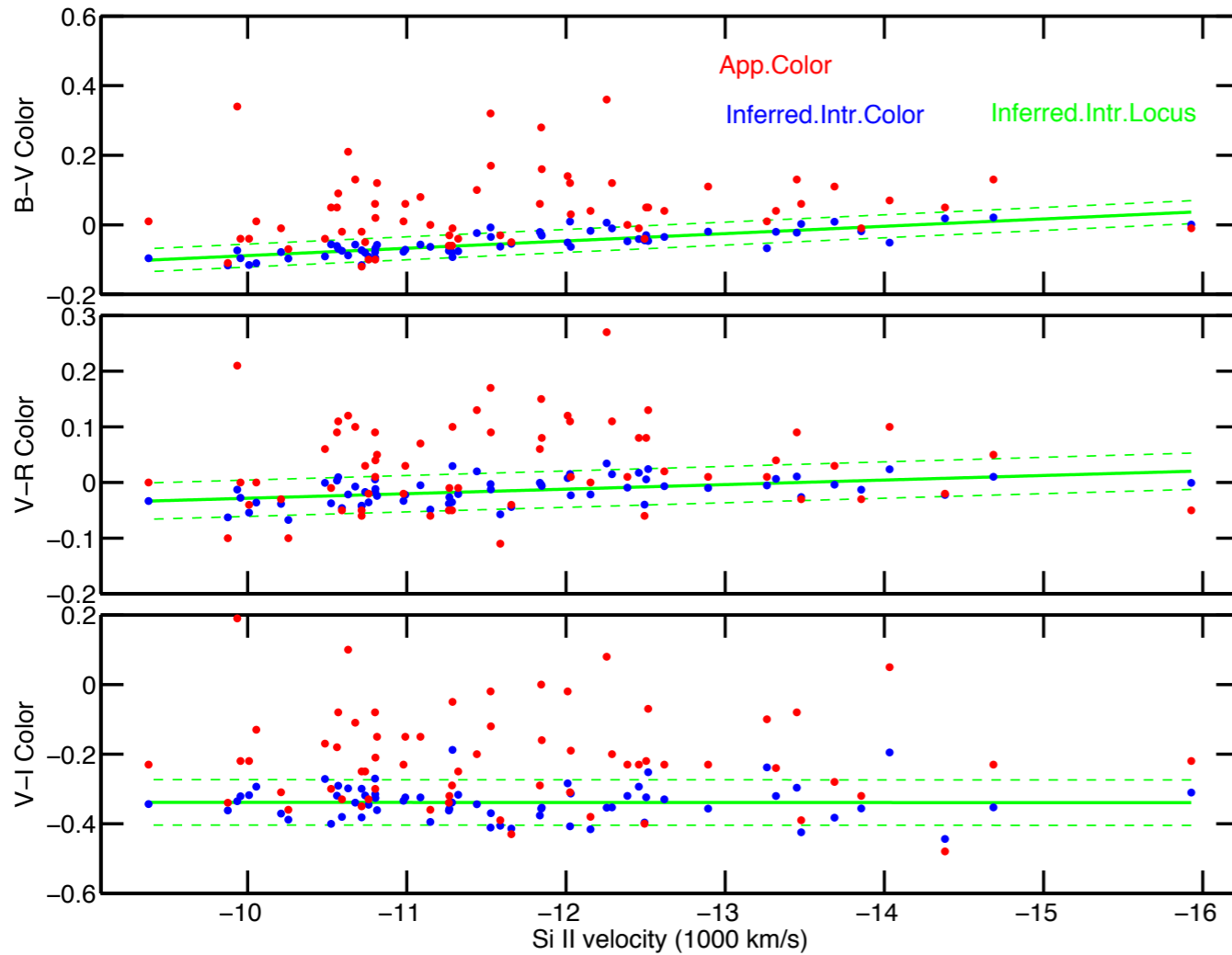
1. Sample Individual SN parameters given data and population hyperparameters
2. Sample hyperparameters given individual parameters



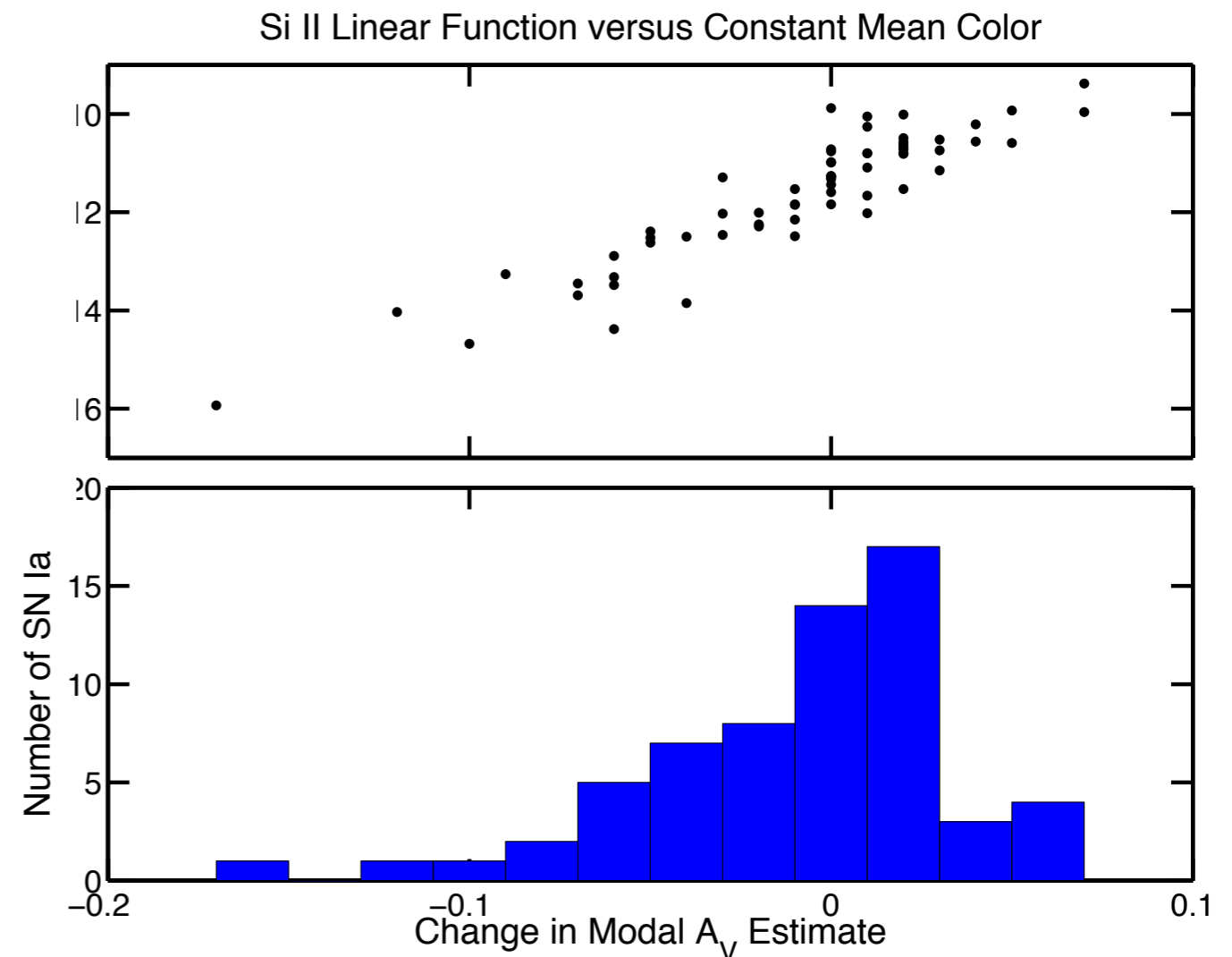
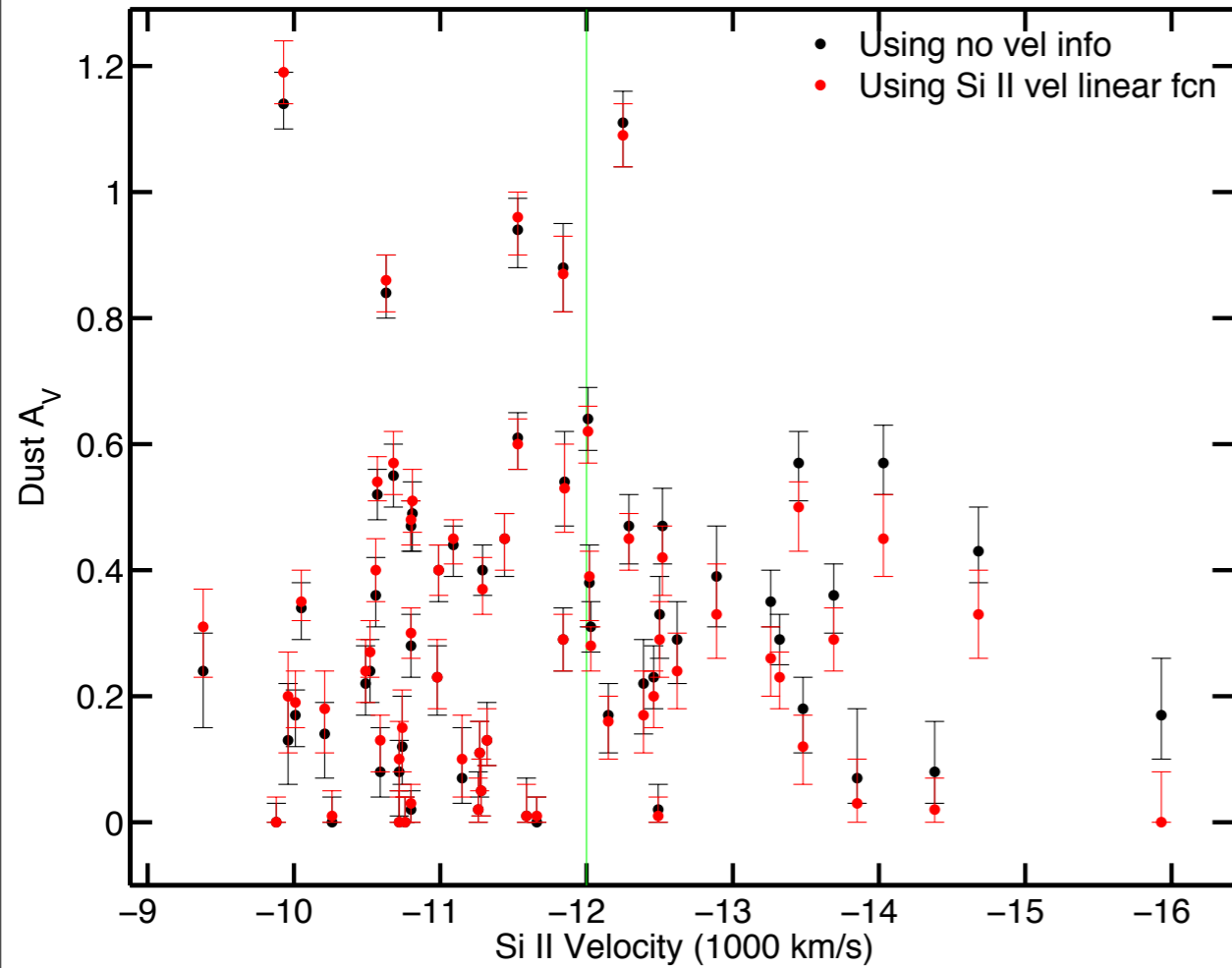
Application to Color-Velocity Data



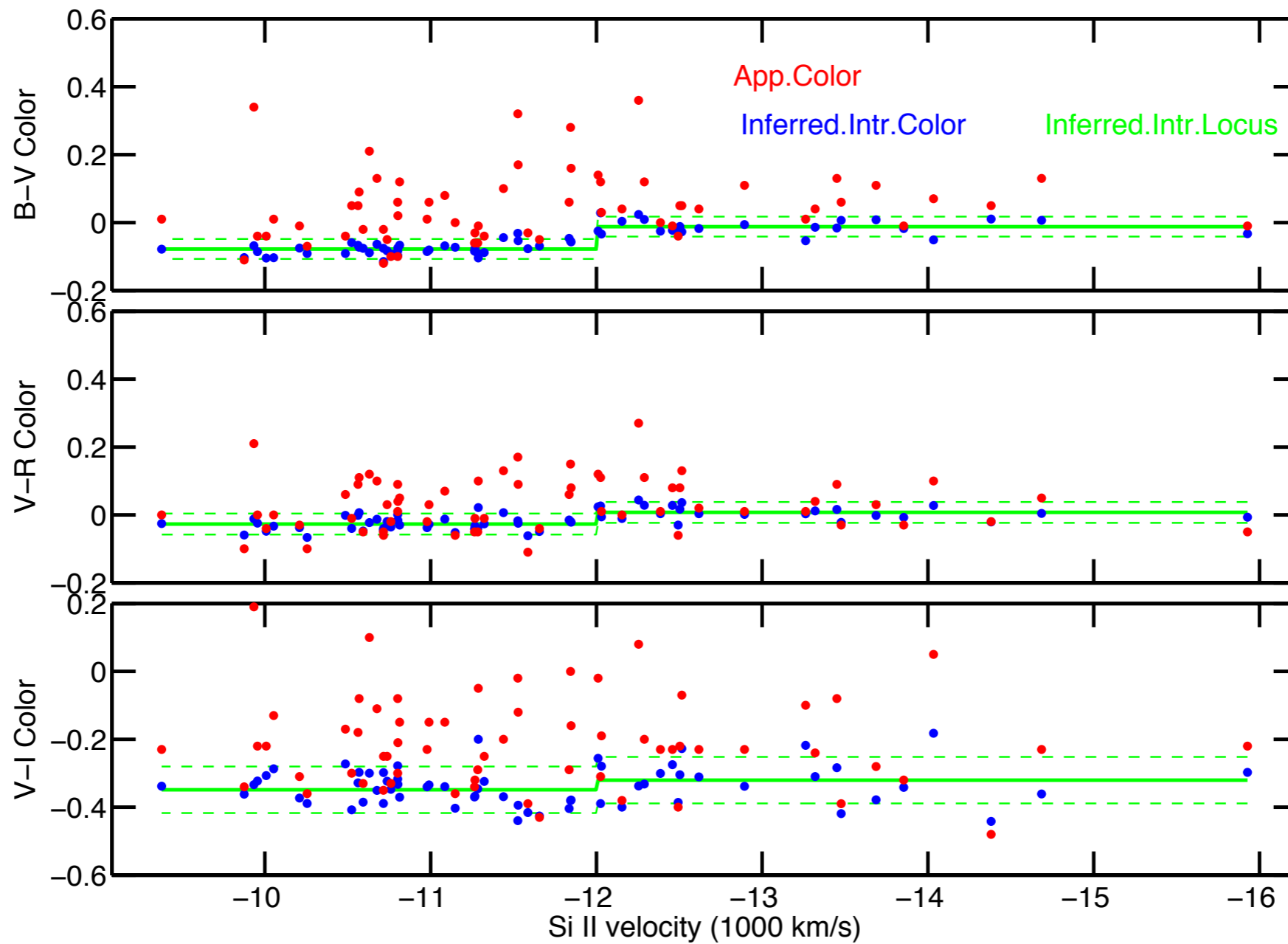
Posterior Inferences: Linear Intrinsic Color-Velocity Function



Leveraging Intrinsic Color-Velocity info changes the Dust Estimates



Posterior Inferences: Step Intrinsic Color-Velocity Function



Model Comparison using Deviance Information Criterion

- How complex a model to fit?
- Penalize the posterior average deviance ($-2 \times \log$ likelihood) by the effective number of parameters
- Uses MCMC samples

Table 3. Information Criteria for Color-Velocity Data

Model	\hat{D}	$\langle D \rangle$	p_D	DIC	Δ_0^a
Const/Gaussian	-780.3	-775.0	5.4	-769.6	0.0
Linear	-790.9	-783.1	7.8	-775.3	-5.7
Step	-791.6	-783.7	7.9	-775.8	-6.2
Quadratic	-799.5	-788.8	10.7	-778.1	-8.5
Cubic	-799.1	-785.6	13.5	-772.1	-2.5

^aDifference in DIC relative to that of the Gaussian (constant mean intrinsic color) model

Conclusion

- Two Applications of Bayesian Modeling applied to Supernova Data
- Naive Bayes Classification of SN using Galaxy Data
- Modeling Intrinsic Color-Velocity trends in presence of dust