SALT methodology

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Supernovae Ia Cosmology: Fitting

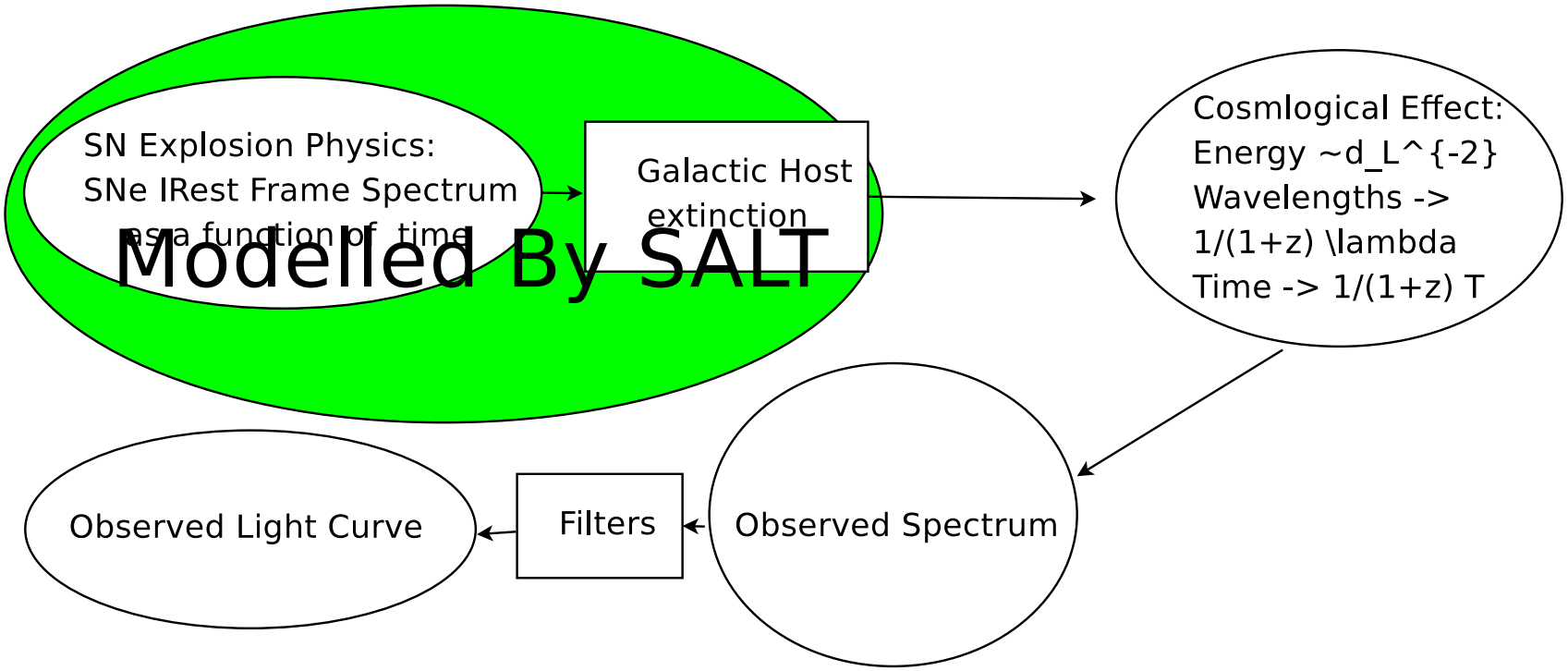
Phenomenological models of light curves

- Studies of trends in observed data
- Ansatz for models of light curves on the basis of such observation
- model parameters evaluated on the basis of well measured supernova samples
- Fit current data to models and obtain cosmological fits and fit errors

SALT: formalizing phenomenological modelling

- Use ansatz to set general guideposts on some constraints and model form
- Train Formal procedure to use training data to find 'best' allowed model
- Fit Using all current data find the values describing properties for each supernova.

SALT: Color Modelling



SALT SED Model

$$F(SN, p, \lambda) = x_0 \left[M_0(p, \lambda) + x_1 M_1(p, \lambda) + ..\right] \exp\left[cCL(\lambda)\right]$$

- p is phase in rest frame since B band maximum
- λ is wavelength in the rest frame
- M_i are sets of spectra that may be regarded as templates. Currently using only M_0 and M_1
- SALT color parameter $c = (B - V)_{MAX} - \langle B - V \rangle$
- SALT Color law $CL(\lambda)$

Training : use data to fix the model form of $M_i(\lambda, p), CL(\lambda)$
Fitting : fit new data to this model: $SN \rightarrow \{(x_0, x_1, c), z\}$

Getting to cosmology: luminosity distance estimates

SALT SED model

$$F(SN, p, \lambda) = x_0 \left[M_0(p, \lambda) + x_1 M_1(p, \lambda) + ..\right] \exp\left[cCL(\lambda)\right]$$

Definitions

$$f_T(t) \sim \frac{1}{d_L^2(z)} \int F(SN, t, \lambda, x_0, x_1, c) T(\lambda) \lambda d\lambda \qquad m_T(t) \sim log(f)$$

$$F_0(t) = \int M_0(\lambda, t) T(\lambda) \lambda d\lambda, \qquad F_1(t) = \int M_1(\lambda, t) T(\lambda) \lambda d\lambda$$

$$\begin{aligned} m_T(t) &\sim \log(x_0 F_0(t)) - 2\log(d_L) + \log(1 + x_1 F_1/F_0) + cCL(\lambda_T) \\ &\approx M_0' - 2\log(d_L) + x_1 \frac{F_1}{F_0} + cCL(\lambda_T) \end{aligned}$$

linear, but correlations/dependence between x_1, x_0, c from emperical derivation

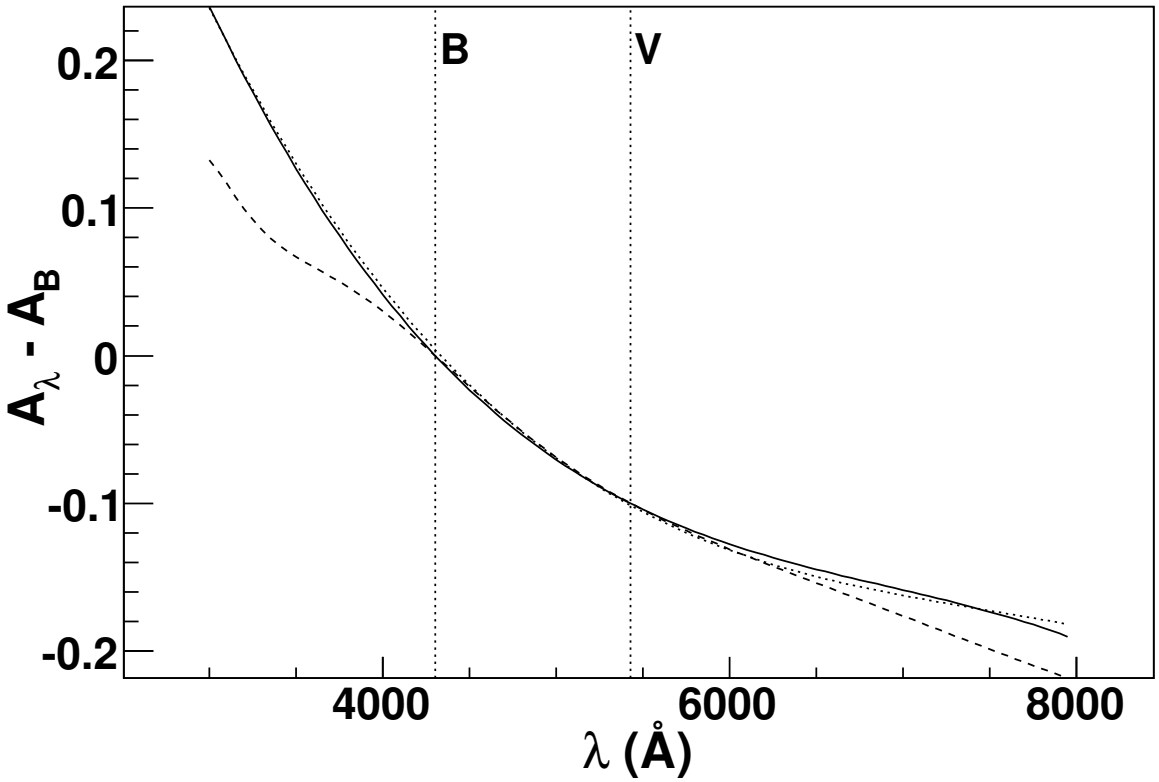
Color Law Details

Need measurements in at least two bands (usually B and V) for implementation of color law constraints:

- Define color parameter $c = (B - V)_{MAX} - \langle B - V \rangle$
- $CL(\lambda_B) = 0, CL(\lambda_V) = 0.4 \log(10)$
- Write in terms of reduced $\Lambda(\lambda) \equiv \frac{\lambda - \lambda_B}{\lambda_B - \lambda_V}$
- $CL(\lambda) = \frac{\Lambda(\lambda)(1 + c_0\Lambda(\lambda) + c_1\Lambda^2(\lambda) + c_2\Lambda^3(\lambda) + c_3\Lambda^4(\lambda))}{1 + c_0 + c_1 + c_2 + c_3}$ (satisfies constraints with free parameters)

Values of c_i are obtained from the training procedure

Color Law similar to Observed Extinction

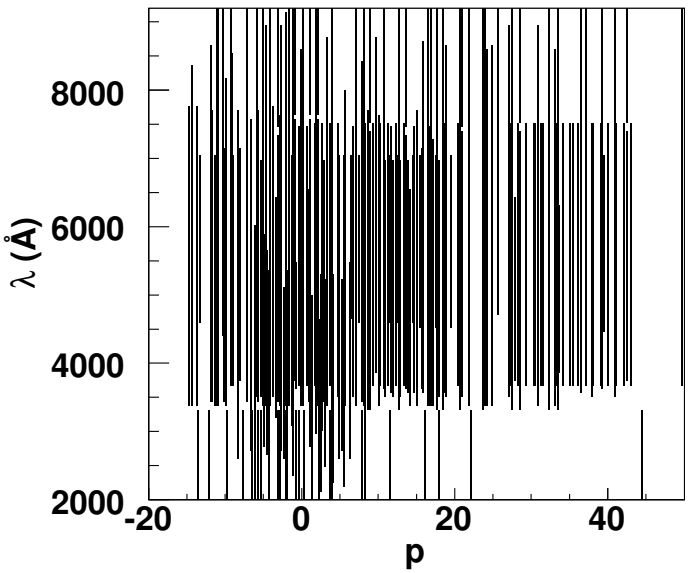


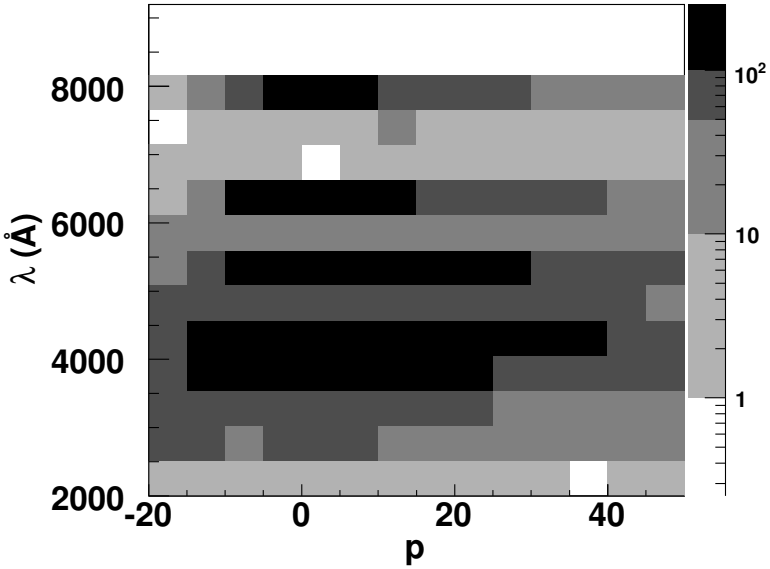
- "solid" : SALT2
- "dashed Cardelli law, $R_v = 3.1, E(B-V) = 0.1$
- "dotted : SALT"

Model Spectra Details

- M_0 :10×120 parameters in $[-20, 50] \times [2000, 9200]$ ie. a spacing of 7×60
- M_1 :10×60 parameters in $[-20, 50] \times [2000, 9200]$ ie. a spacing of 7×120
- Extremely large number of parameters to fix by training

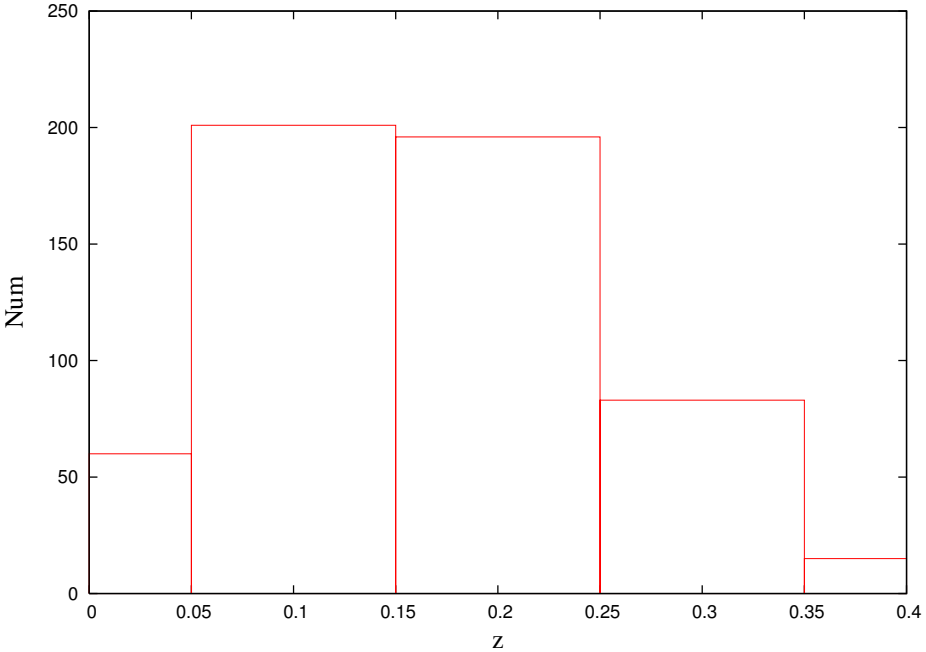
Coverage in Guy etal 07



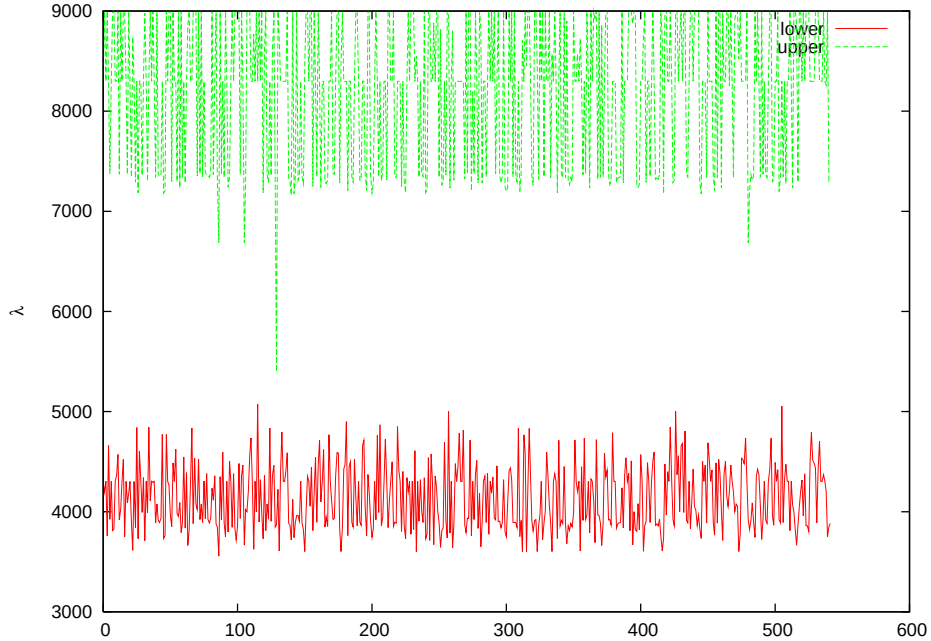


- Training is an iterative process of minimizing deviations of the model surface to training sample data
- Training data did not exist in the entire phase space of the model. Addressed by spline interpolation of available data.
- Tendency for overfitting available data avoided by various regularization schemes.
- Finally, address this by gathering more data (eg. SDSS), but understand performance based on studies on simulations (Jennifer's talk)

SDSS data

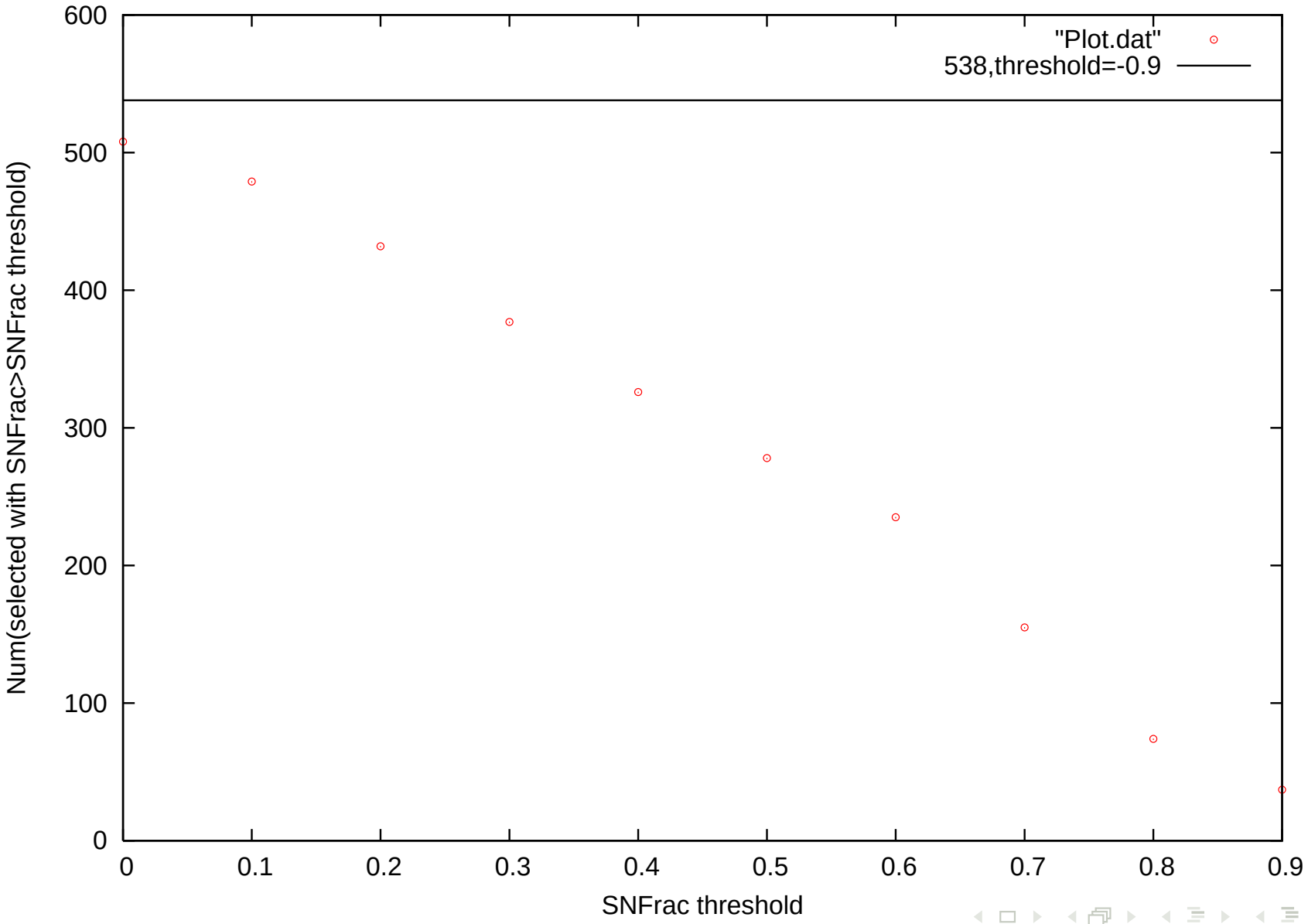


Lightcurves :
redshift distribution



Spectra from SDSS

SDSS spectra:Quality



Current Status

- Have just received SNLS data and compatible training code which can been used on it.
- SDSS data format conversions: changes to enable possible future cuts. Probably close to being complete.
- Expect to run training on SNLS and then SDSS in the next few days

Training Procedure

$$\chi^2 \equiv \sum_i (D_i - M_i(\theta))^T W_i (D_i - M_i(\theta)) + \mathrm{regul}$$

- Start with a first guess θ_0
- $\chi^2 \approx \sum (R_i(\theta_0) - H_i^T \delta\theta)^T W_i (R(\theta_0) - H_i^T \delta\theta) + \mathrm{regul}$

Regularization Procedure

$$\chi^2 = \chi^2_{TrainingSample} + \chi^2_{reg}$$

Use the χ^2_{reg} term to put a prior on how much quantities vary

Regularization terms

$$\chi^2_{reg} = \frac{w}{N} \sum_{i,j} \left(\frac{M_{i,j+1} - M_{i,j}}{\bar{M} \cdot (\lambda_{j+1} - \lambda_j)} \right)^2 \quad (1)$$

$$\chi^2_{reg} = \frac{w}{N} \sum_{i,j} \left(\frac{M_{i+1,j} - M_{i,j}}{\bar{M} \cdot (p_{j+1} - p_j)} \right)^2 \quad (2)$$

$$\chi^2_{reg} = \frac{w}{N} \sum_{i,j} \left(\frac{M_{i+1,j+1} M_{i,j} - M_{i+1,j} M_{i,j+1}}{\bar{M}^2 \cdot (\lambda_{j+1} - \lambda_j)(p_{i+1} - p_i)} \right)^2 \quad (3)$$