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Uncertainty of Refined Seismic Arrival Times

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What are we fundamentally doing?

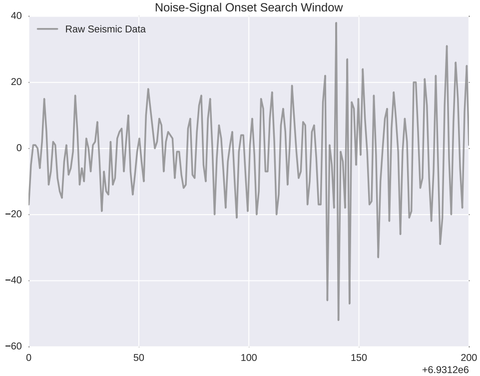


Figure: Onset Search Window output from STA/LTA algorithm

Sliding Window Approach to Estimating Arrival Time

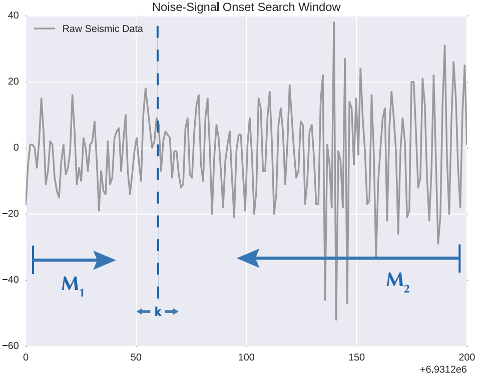


Figure: Fit Models Across Onset Search Window

What Models Do We Fit?

$\mathcal{M}_1$ is Gaussian White Noise:

$$Y_t \sim N(0, \sigma_n^2) \tag{1}$$

$\mathcal{M}_2$ is Auto-Regressive Moving Average, ARMA(p,q):

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t \tag{2}$$

What Do The Models Look Like?

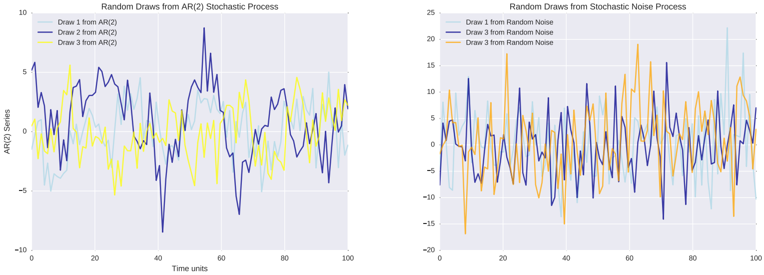
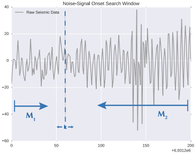


Figure: Samples from: (Left) ARMA Process and (Right) Gaussian White Noise

Find 'k' that Gives "Best Fit"



by minimizing:

$$AIC(\mathcal{M}) = -2\log\mathcal{L}(\mathcal{M}) + 2\rho(\mathcal{M}) \tag{3}$$

where $\mathcal{L}(\mathcal{M})$ is the likelihood of model $\mathcal{M}$, and $\rho(\mathcal{M})$ is the complexity of the model (e.g. degrees of freedom).

$$\mathcal{L}(\mathcal{M}_2) = -\frac{T-k}{2}\ln(2\pi) - \frac{1}{2}\ln\left(\frac{\sigma_s^2}{1-\phi^2}\right) - \frac{1-\phi^2}{2\sigma_s^2}\left(y_{k+1} - \frac{c}{1-\phi}\right)^2 - \frac{(T-k-1)}{2}\ln(\sigma_s^2) - \frac{1}{2\sigma_s^2}\sum_{t=k+2}^{T}(y_t - c - \phi y_{t-1})^2 \tag{4}$$

Find 'k' that Gives "Best Fit"

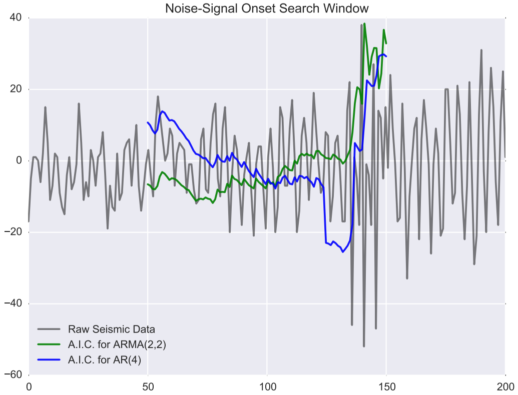


Figure: Arrival Time is 'k' that Gives Lowest AIC

Can we get a Probability Density around our Pick?

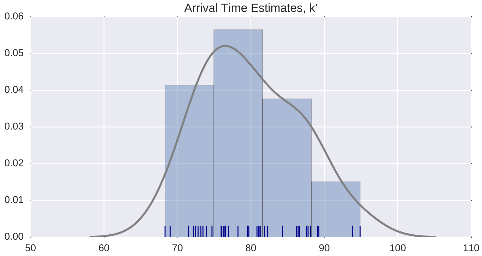


Figure: Estimation of Uncertainty of Arrival Time

Imagine a second sensor sitting in same room– could have recorded the following signal:

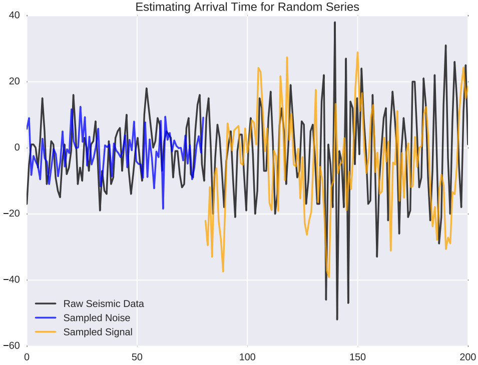
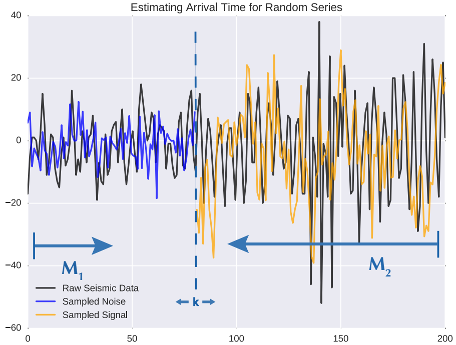


Figure: A Different Realization of Underlying Process

Idea: What We Observe Was Random Realization of Underlying Process

Generate New Data!

Run Algorithm Again!

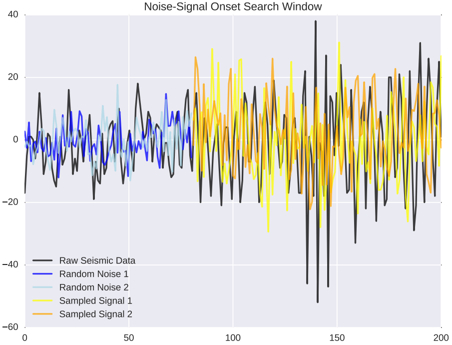


Idea: What We Observe Was a Random Realization of Underlying Process

Generate New Data!

Run Algorithm Again!

And Do it Again -and- Again!



Idea: What We Observe Was a Random Realization of Underlying Process

Generate New Data!

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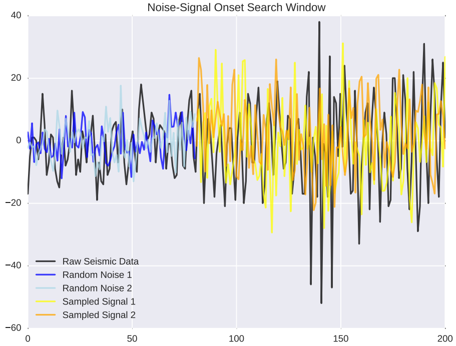
In statistical literature, this is known as **Parametric Bootstrap Resampling**.



We get a Probability Density around our Pick!

All of Our Arrival Time Picks Create an Uncertainty Estimate!

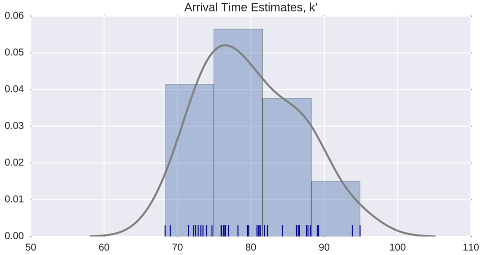


Figure: Estimation of Uncertainty of Arrival Time

We get a Probability Density around our Pick!

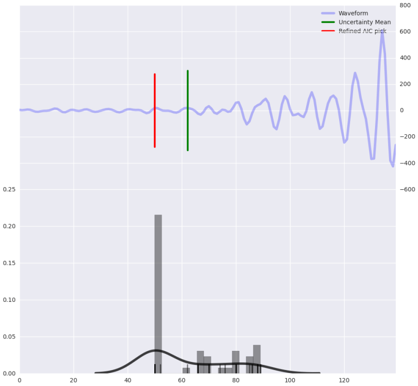


Figure: Refined Pick + Uncertainty of Arrival Time

Why should we care about Uncertainty?

Do humans always select the same arrival?

Why should we care about Uncertainty?

Better downstream analyses incorporate uncertainty:

1. multiple event relocation
2. event associations

We Compare to Human Analysts

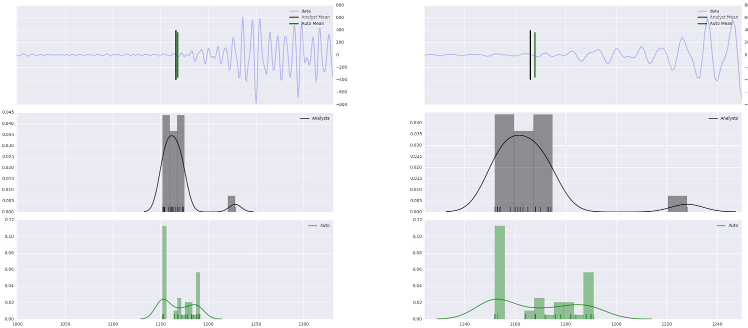


Figure: Estimate from 50 Sampled Waveforms.

We Compare to Human Analysts

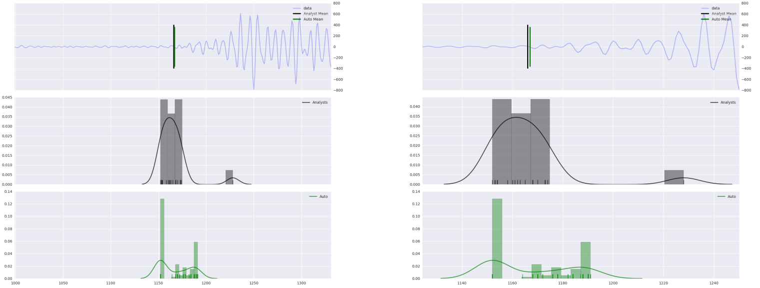


Figure: Estimate from 100 Sampled Waveforms.

Model Uncertainty and Data-Driven Choices

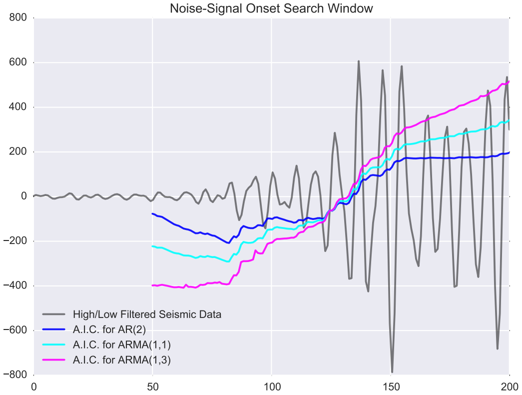


Figure: Different Models Find Different Arrivals

Model Uncertainty and Data-Driven Choices

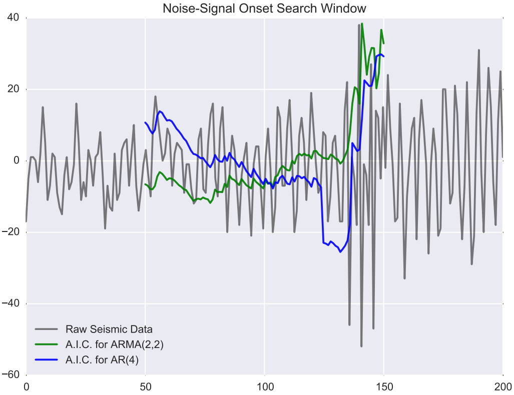


Figure: Different Models Find Different Arrivals