Approximate Inference in Industry: Two Applications at Amazon

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Neural Information Processing Systems, 2017

Amazon.com, 2017

Today, machine learning is creating a paradigm shift.

"It is a golden age. Machine learning and AI is a horizontal enabling layer. It will empower and improve every business, every government organization, every philanthropy."

Jeff Bezos in Geekwire (May 6, 2017)

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$$1 + 1 =$$

$$[(27/3)/3] - 1$$

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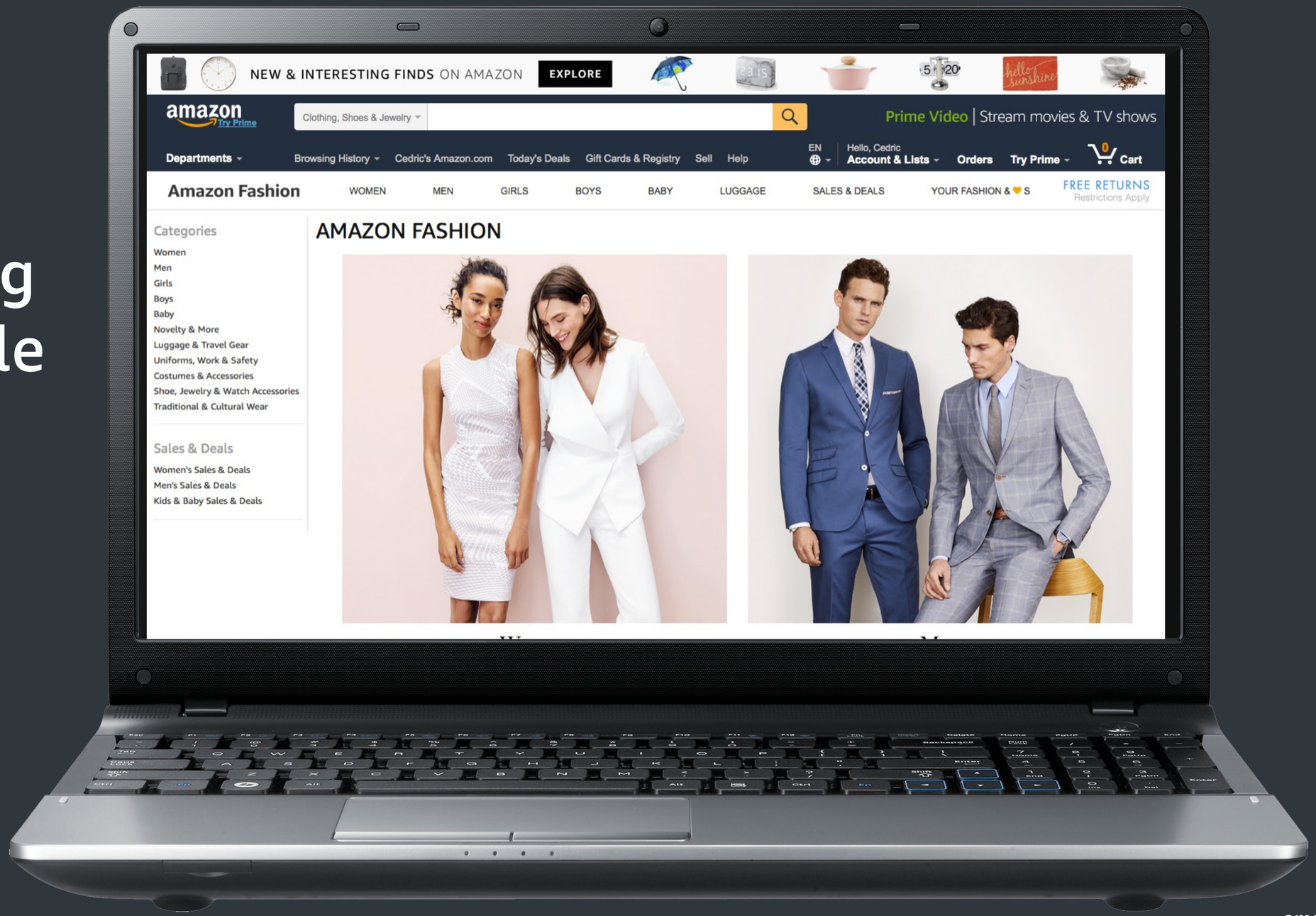
Understanding Fashion & Style



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Hair Drawing #4

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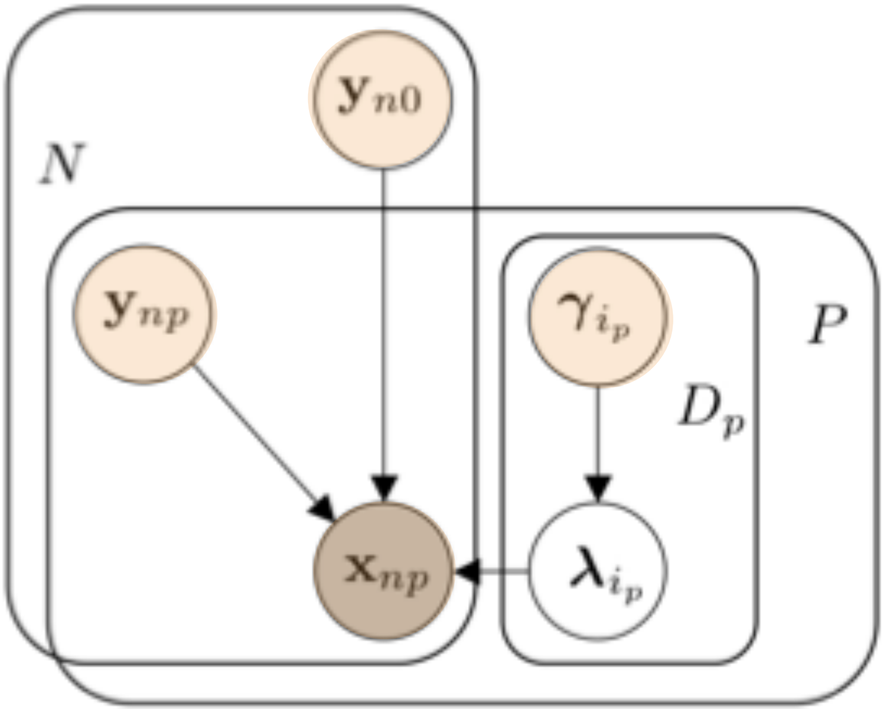

(Archambeau and Bach, NIPS 2008)

Shallow Latent Variable Model

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Variational Inference

- Using *Jensen's inequality*, we get for any distribution $q_{\mathbf{w}}(\mathbf{Z}, \boldsymbol{\theta})$:

$$\begin{aligned}
\ln p(\mathbf{X}) &= \ln \iint p(\mathbf{X}, \mathbf{Z}, \boldsymbol{\theta}) \, d\mathbf{Z} \, d\boldsymbol{\theta} \\
&\geqslant \iint q_{\mathbf{w}}(\mathbf{Z}, \boldsymbol{\theta}) \ln \frac{p(\mathbf{X}, \mathbf{Z}, \boldsymbol{\theta})}{q_{\mathbf{w}}(\mathbf{Z}, \boldsymbol{\theta})} \, d\mathbf{Z} \, d\boldsymbol{\theta} \\
&= \ln p(\mathbf{X}) - \mathrm{KL}[q_{\mathbf{w}}(\mathbf{Z}, \boldsymbol{\theta}) \| p(\mathbf{Z}, \boldsymbol{\theta} | \mathbf{X})] \triangleq -\mathcal{F}(\mathbf{w}).
\end{aligned}$$

- A tractable solution is found by assuming $q_{\mathbf{w}}$ factorises given the data:

$$q_{\mathbf{w}}(\mathbf{Z}, \boldsymbol{\theta}) = \prod_n q(\mathbf{z}_n; \mathbf{w}_n) \times \prod_m q(\boldsymbol{\theta}_m; \mathbf{w}_m).$$

(Beal, 2000)

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Stochastic Variational Inference

$$\mathbf{w}_n \leftarrow \arg\max_{\mathbf{w}_n} \quad \langle \ln p(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}) \rangle - \mathrm{KL}\left[q(\mathbf{z}_n; \mathbf{w}_n) \| p(\mathbf{z}_n)\right],$$

$$\mathbf{w}_m \leftarrow \arg\max_{\mathbf{w}_m} \quad \sum_n \langle \ln p(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}) \rangle - \mathrm{KL}\left[q(\boldsymbol{\theta}_m; \mathbf{w}_m) \| p(\boldsymbol{\theta}_m)\right].$$

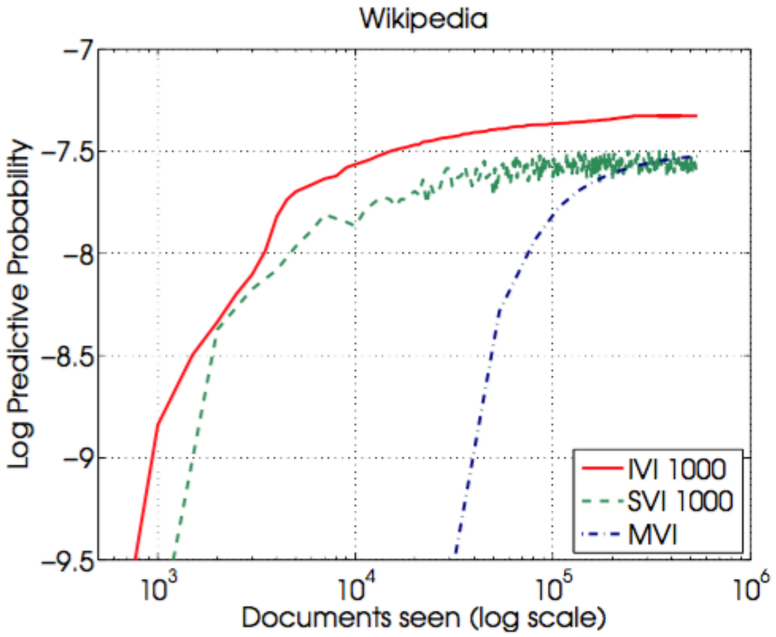
Let $\ell_n(\mathbf{w}) = \langle \ln p(\mathbf{x}_n|\mathbf{z}_n, \boldsymbol{\theta}) \rangle$:

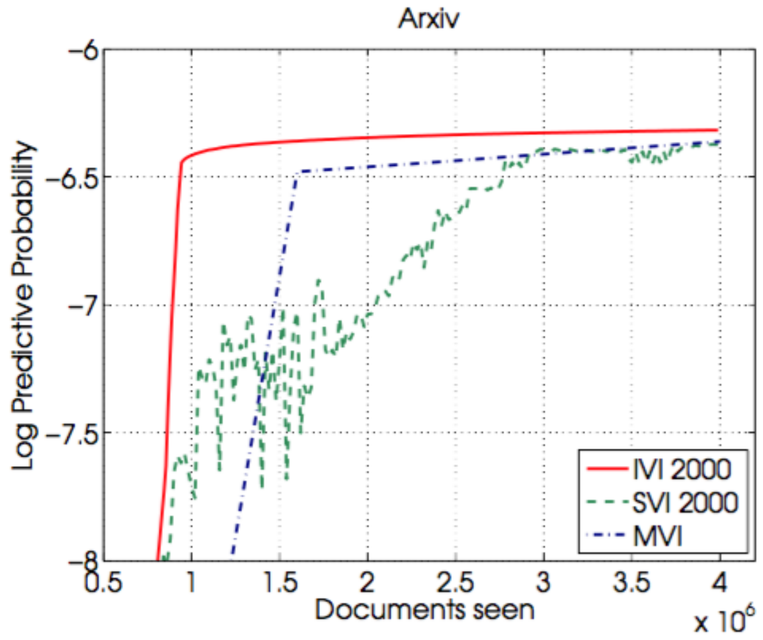
$$\mathbf{w}_m \leftarrow \mathbf{w}_m + \rho_t N \frac{\partial}{\partial \mathbf{w}_m} \left(\ell_n(\mathbf{w}) - \frac{\mathrm{KL}\left[q(\boldsymbol{\theta}_m; \mathbf{w}_m) \| p(\boldsymbol{\theta}_m)\right]}{N} \right),$$

where $\sum_t \rho_t = \infty$ and $\sum_t \rho_t^2 < \infty$.

(Hoffman, et al., NIPS 2010)

Incremental Variational Inference





(Hinton & Neal, 1998; Schmidt, et al., 2013; Archambeau & Ermis, AABI@NIPS 2015)

Demand Forecasting

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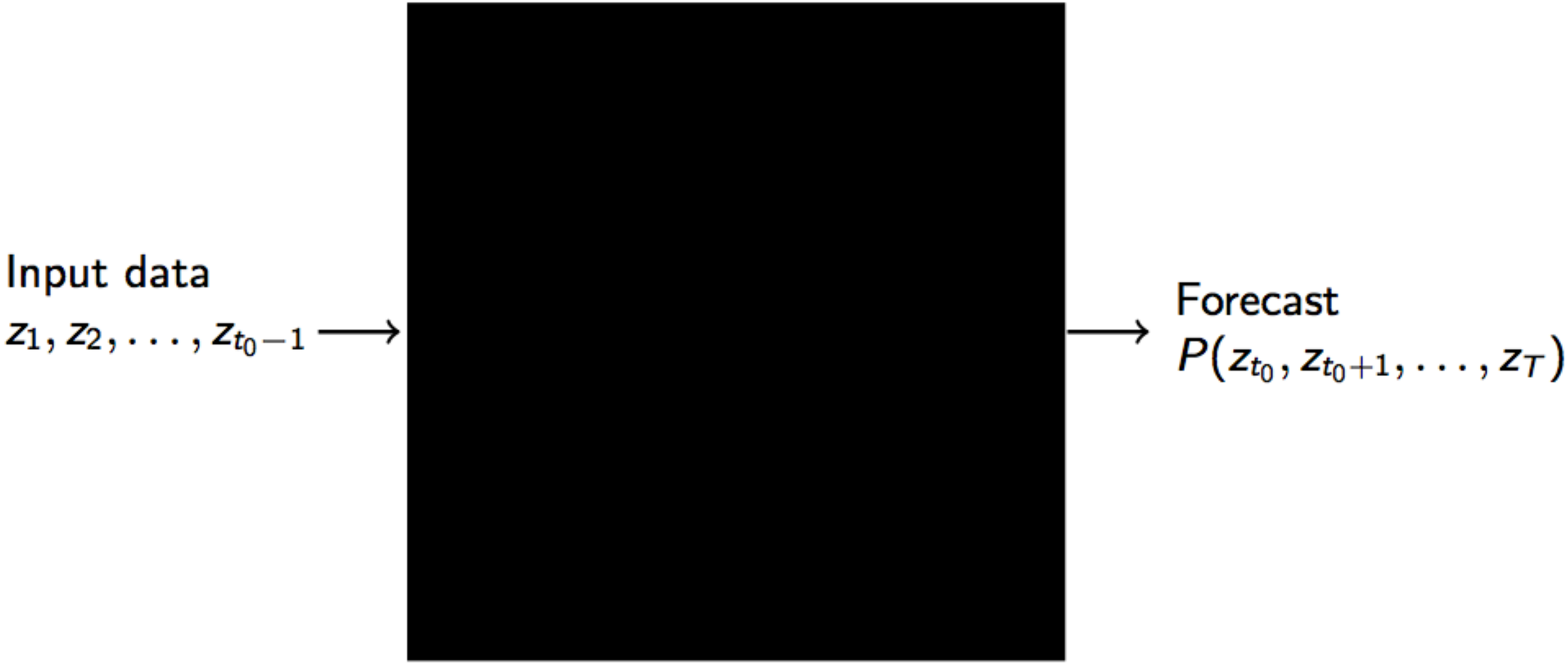
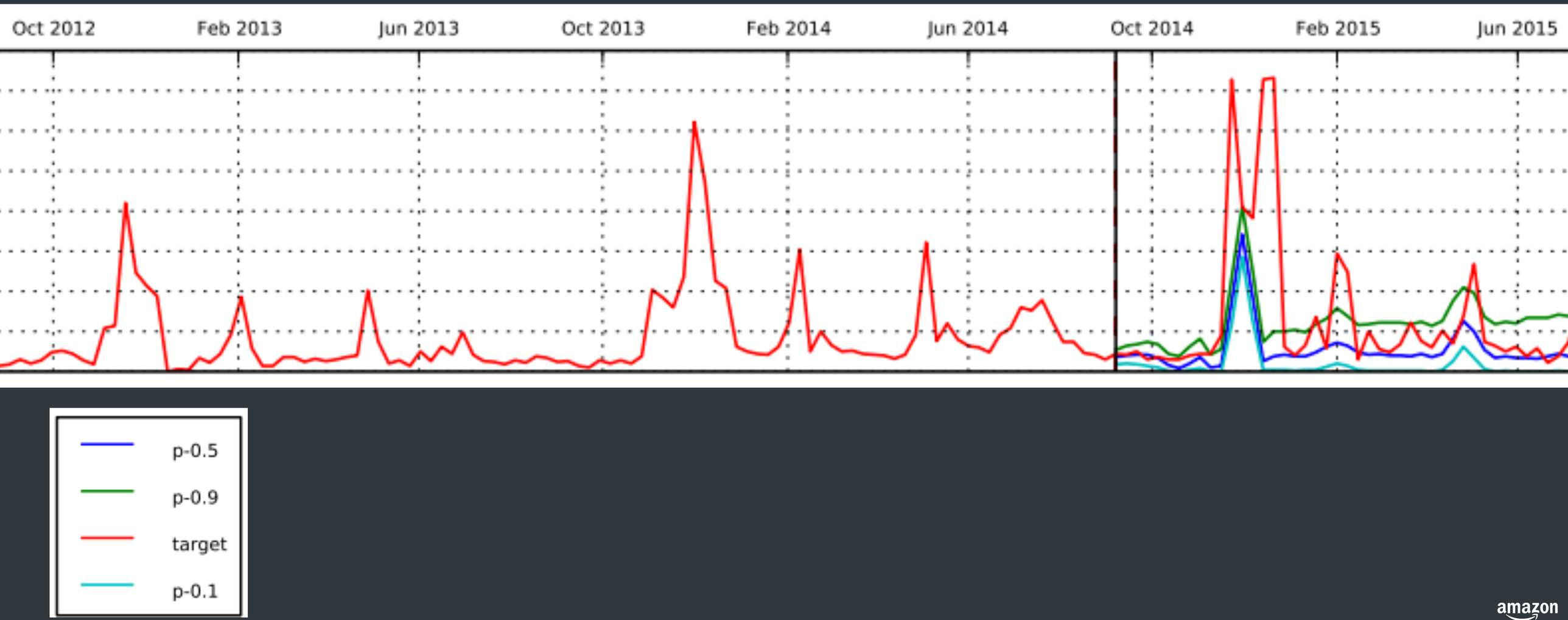
Forecasting



Seasonality and External Events



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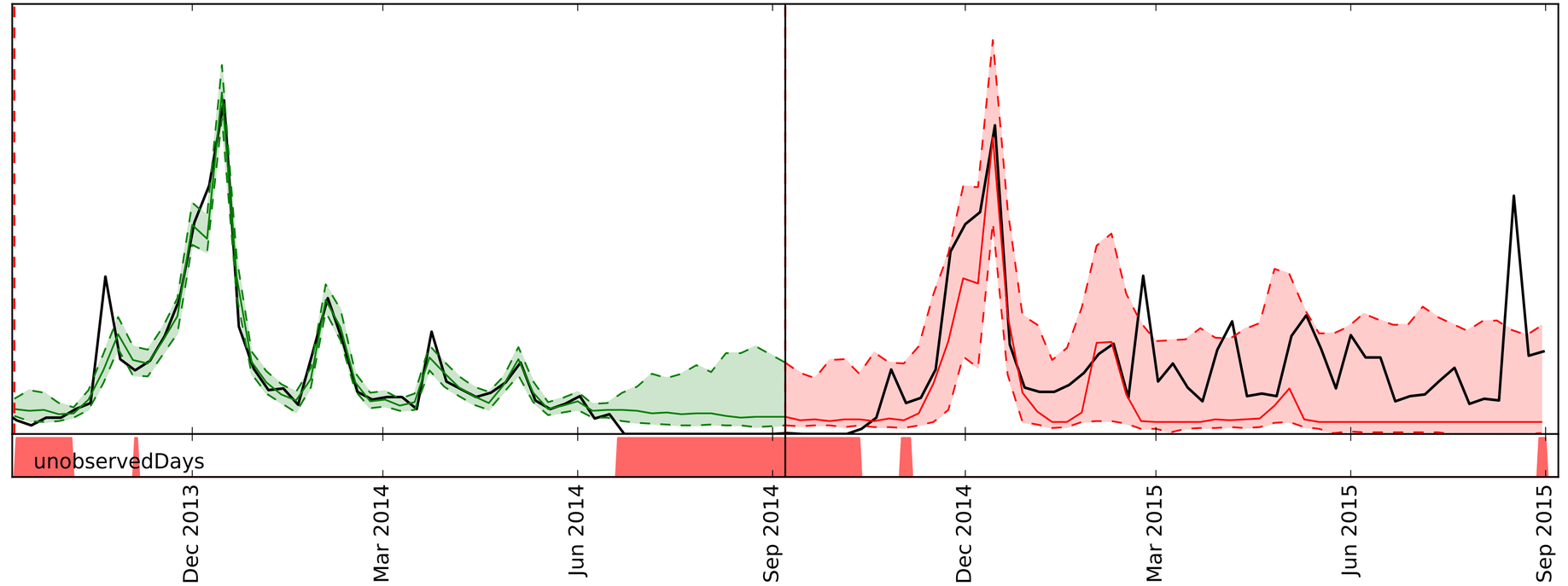

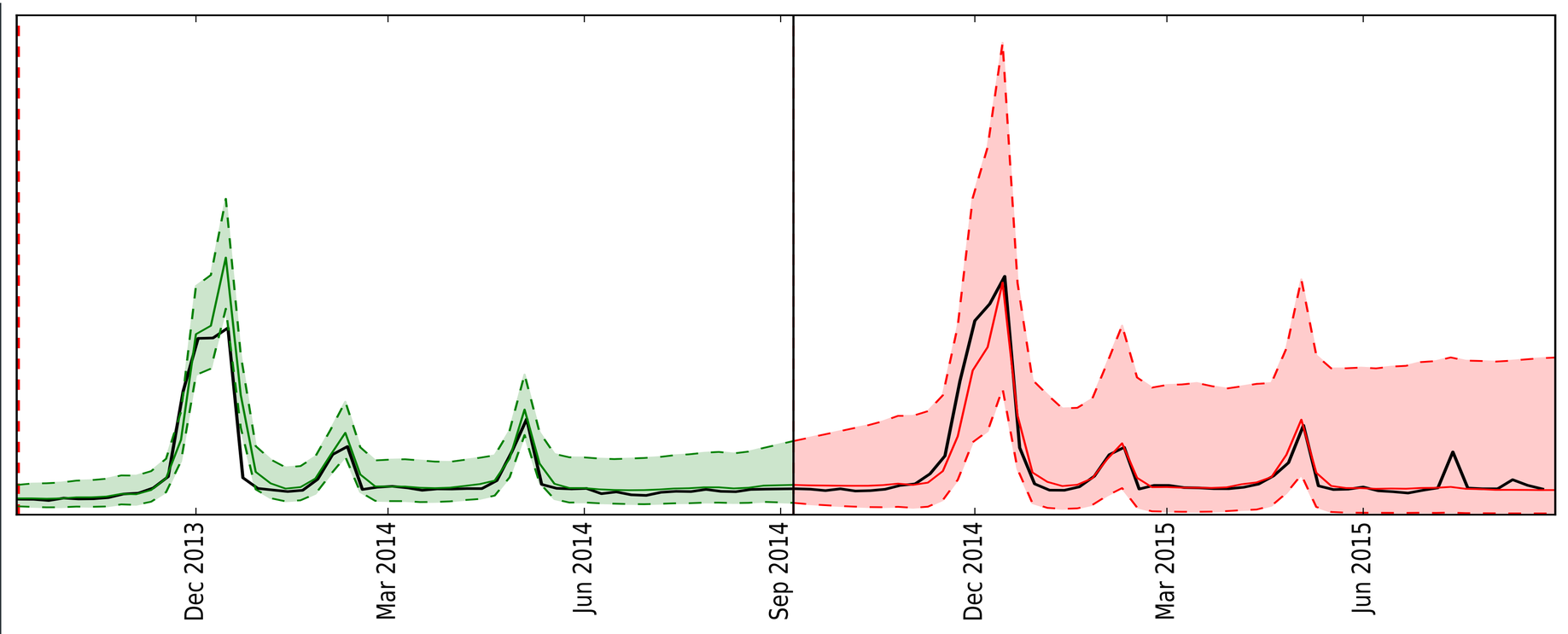

Probabilistic Forecasts

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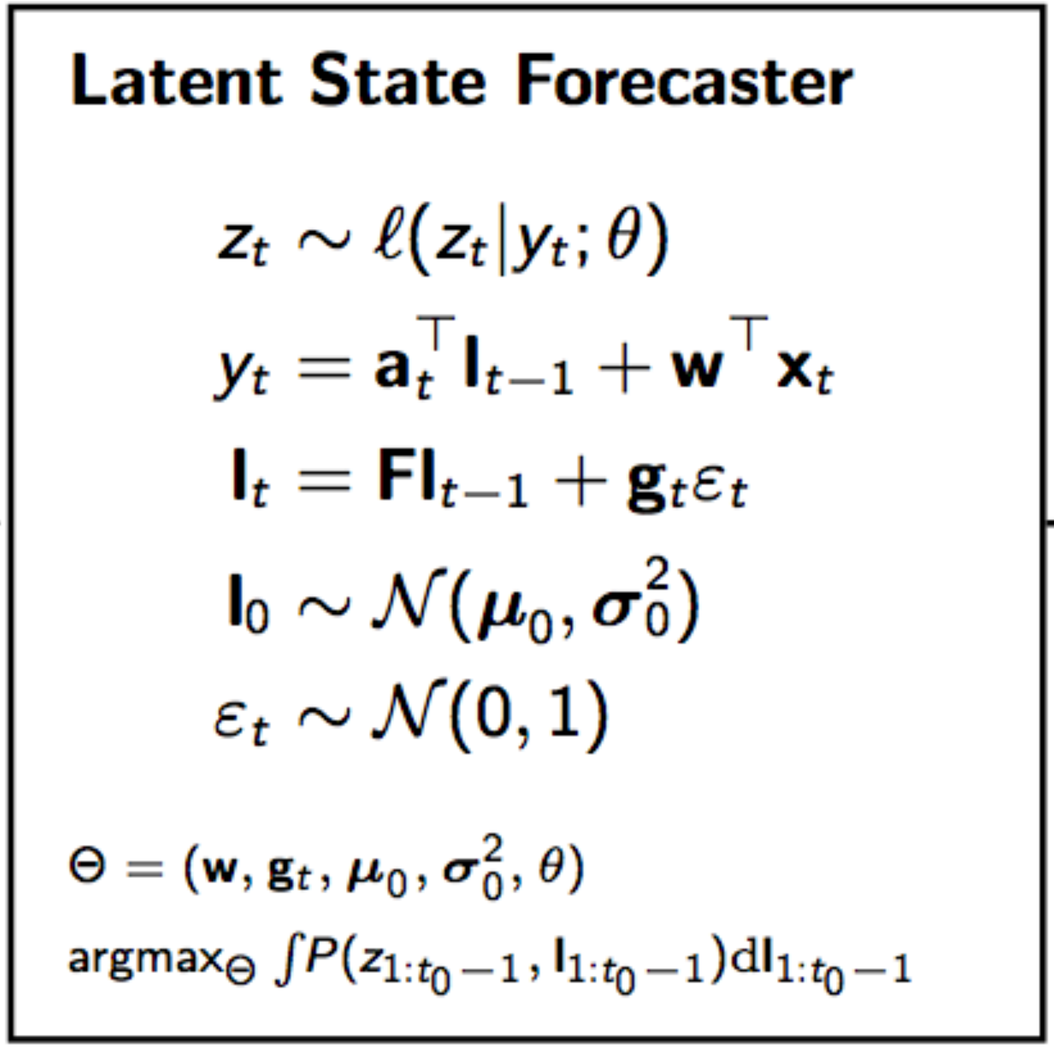
Input data

$z_1, z_2, \ldots, z_{t_0-1}$

$\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T$



Forecast

$P(z_{t_0}, z_{t_0+1}, \ldots, z_T)$

(Seeger, et al.: Bayesian Intermittent Demand Forecasting for Large Inventories. NIPS 2016.)

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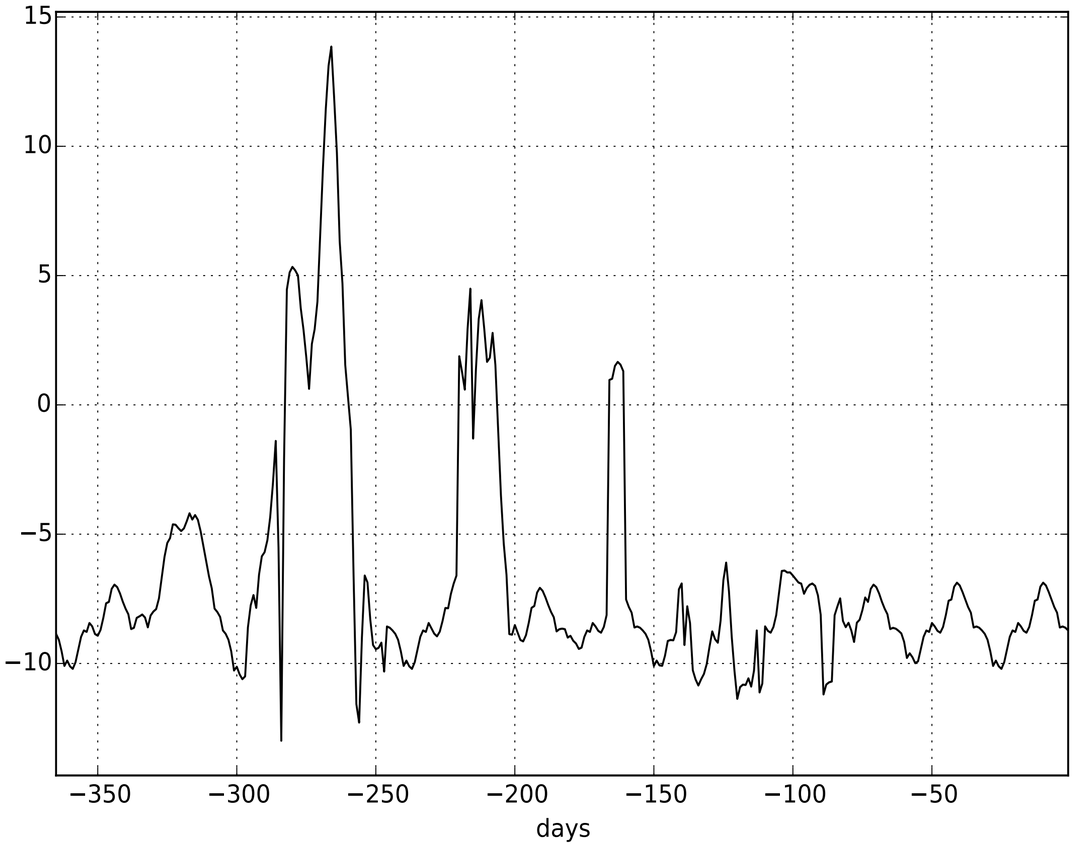
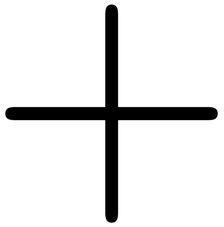
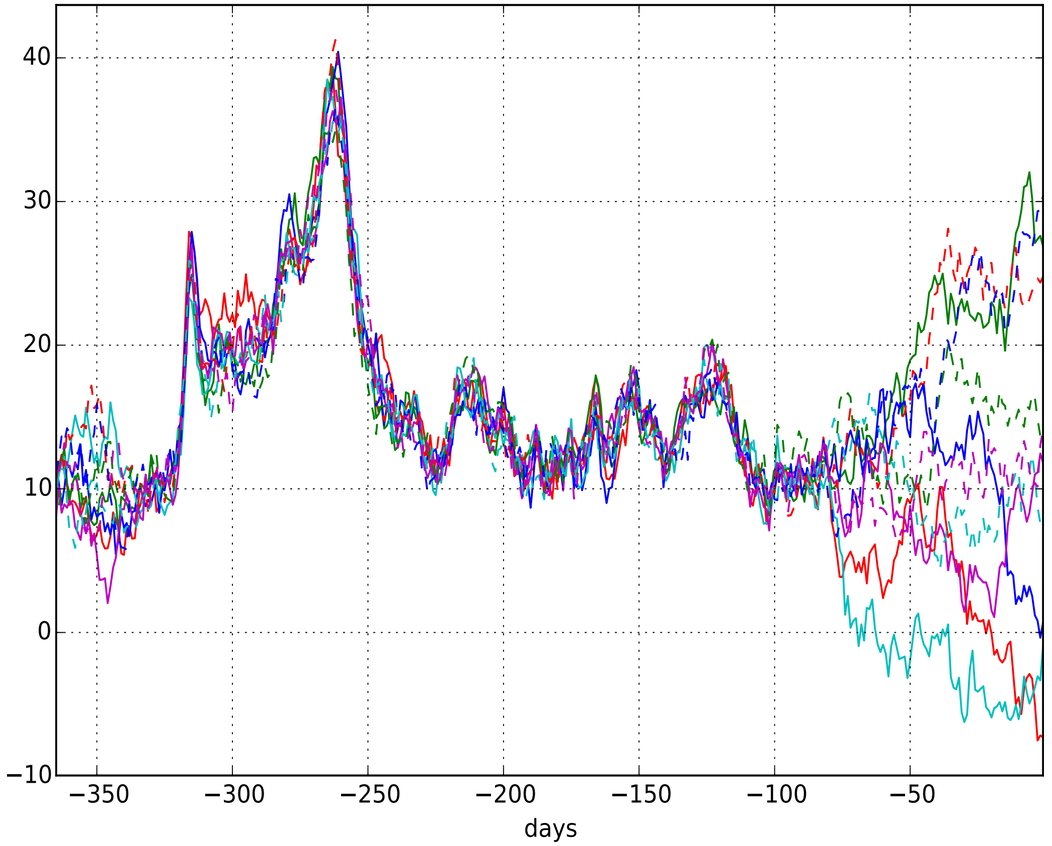
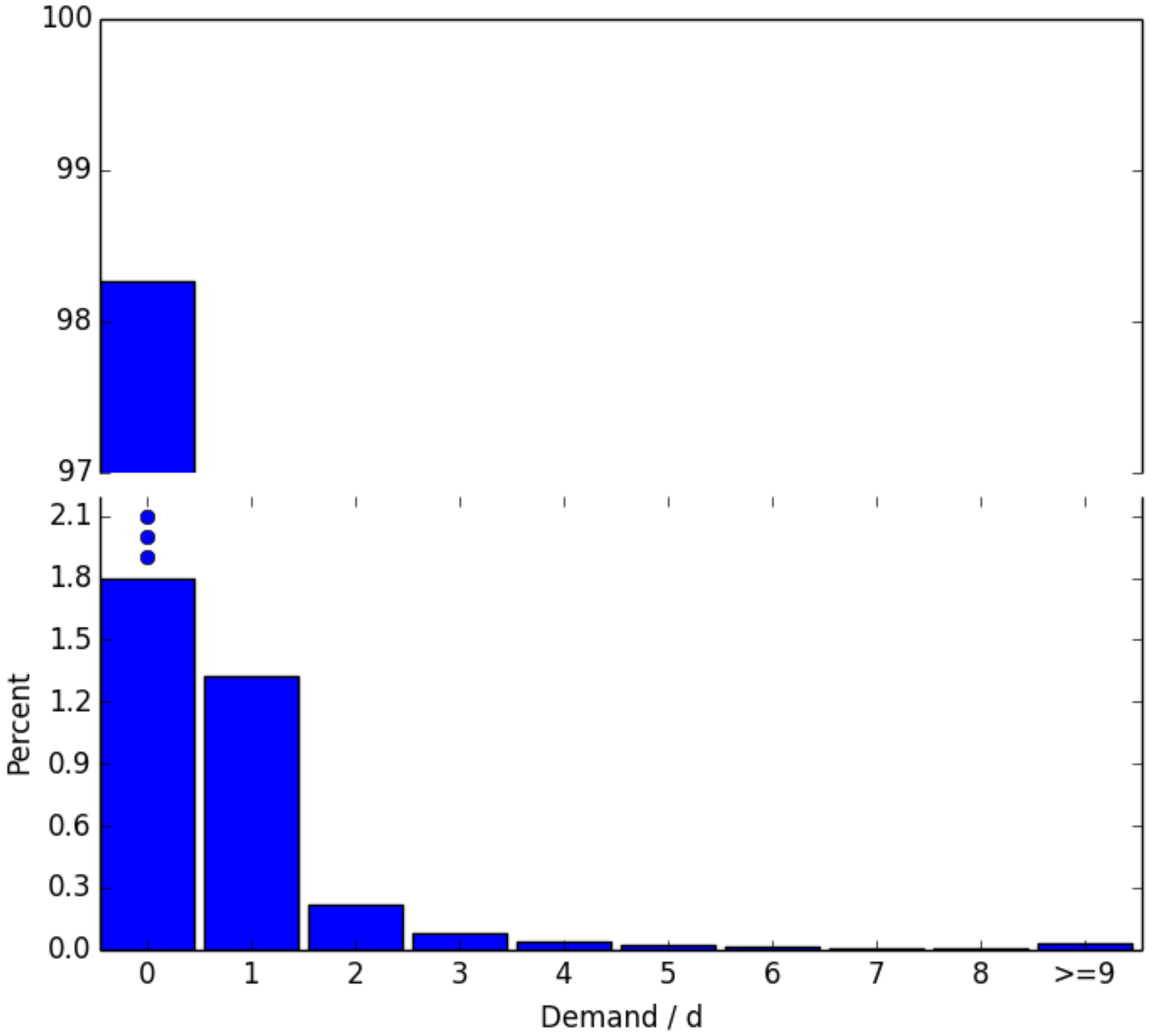
Latent Gaussian State









Intermittent Demand

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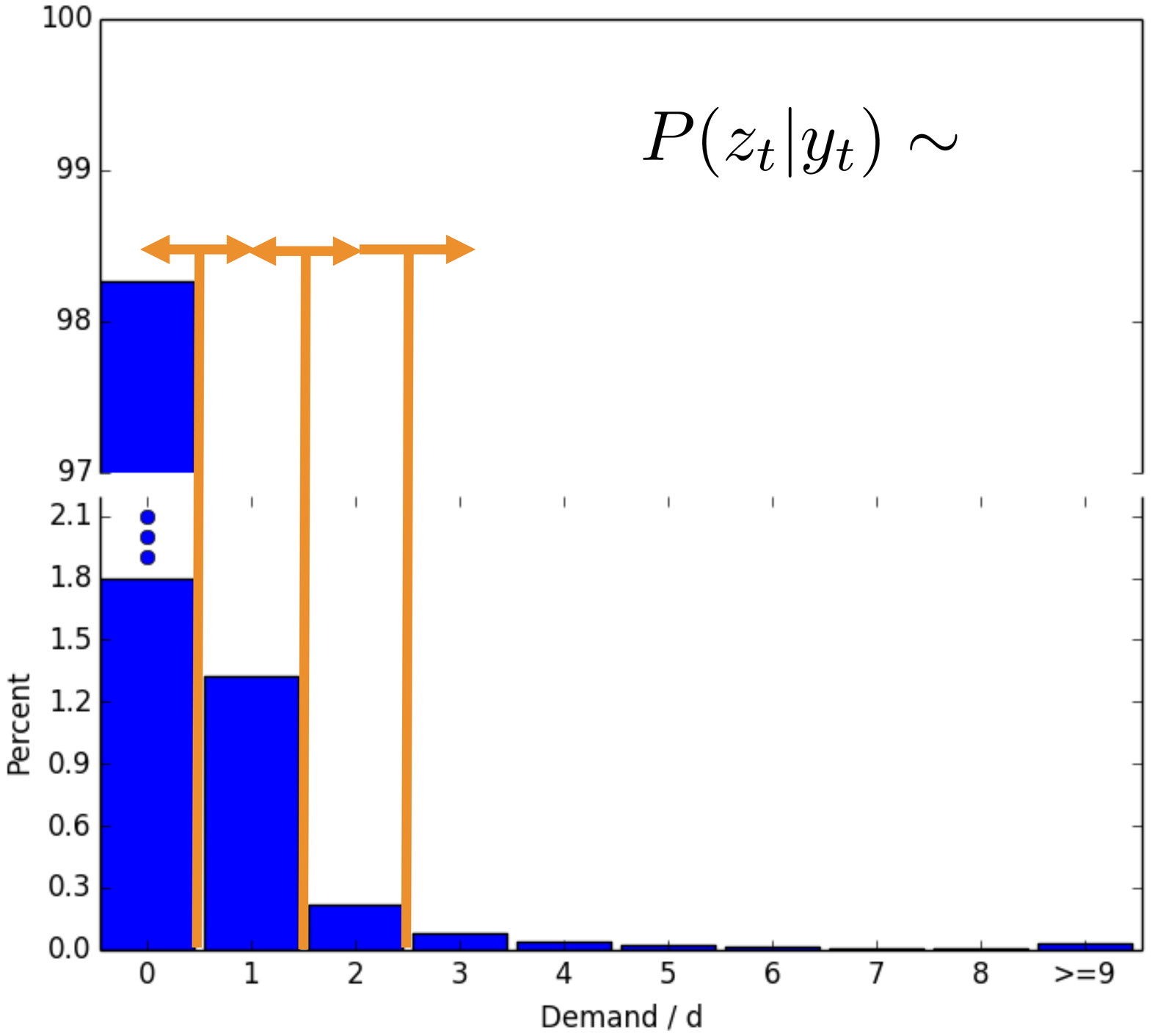

Multi-stage Likelihood

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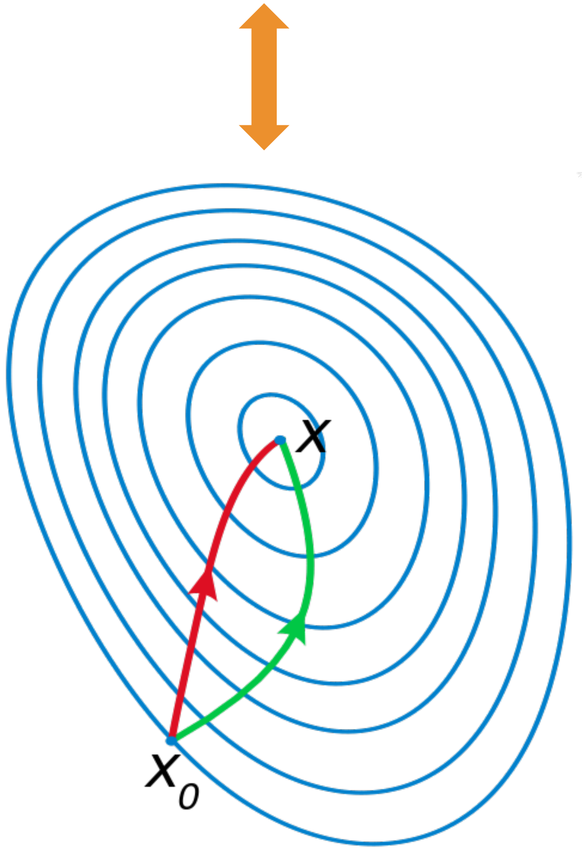
Scalable Inference

```
while (!converged) {

    b = kalmanSmoothing(a)

    a = glueCode(b)

}
```

$$\phi(\theta) = -\log \int P(\mathbf{z}_{\text{train}}, \mathbf{s} \,|\, \theta)\, d\mathbf{s}$$

$$[\Phi(\theta), \nabla_\theta \Phi]$$



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	Parts	EC-sub	EC-all
# items	19874	39700	534884
Unit t	month	day	day
Median CV^2	2.4	5.8	9.7
Freq. $z_t = 0$	54%	46%	83%
In-stock ratio	100%	73%	71%
Avg. size series	33	329	293
# item-days	656K	13M	157M

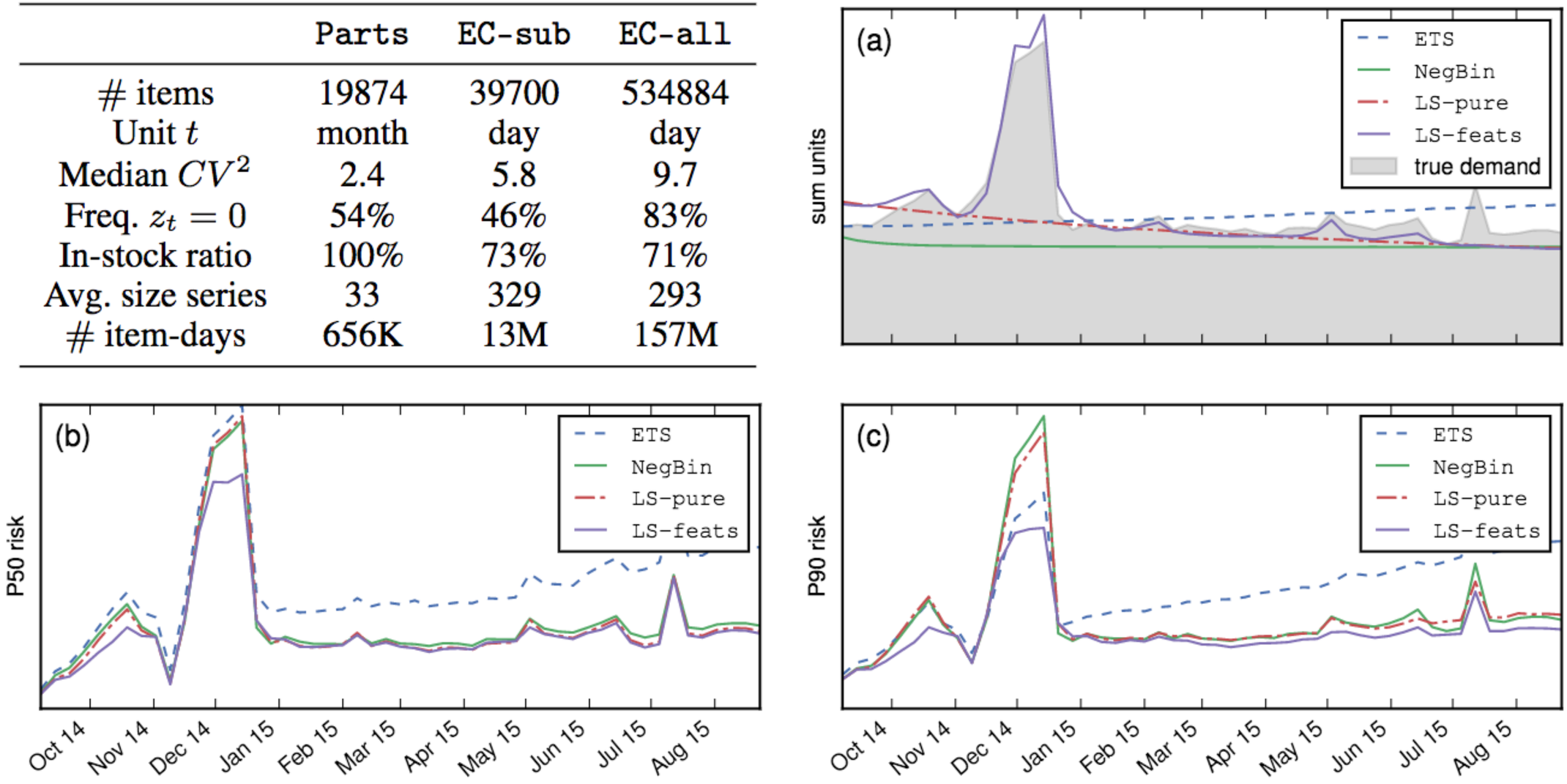


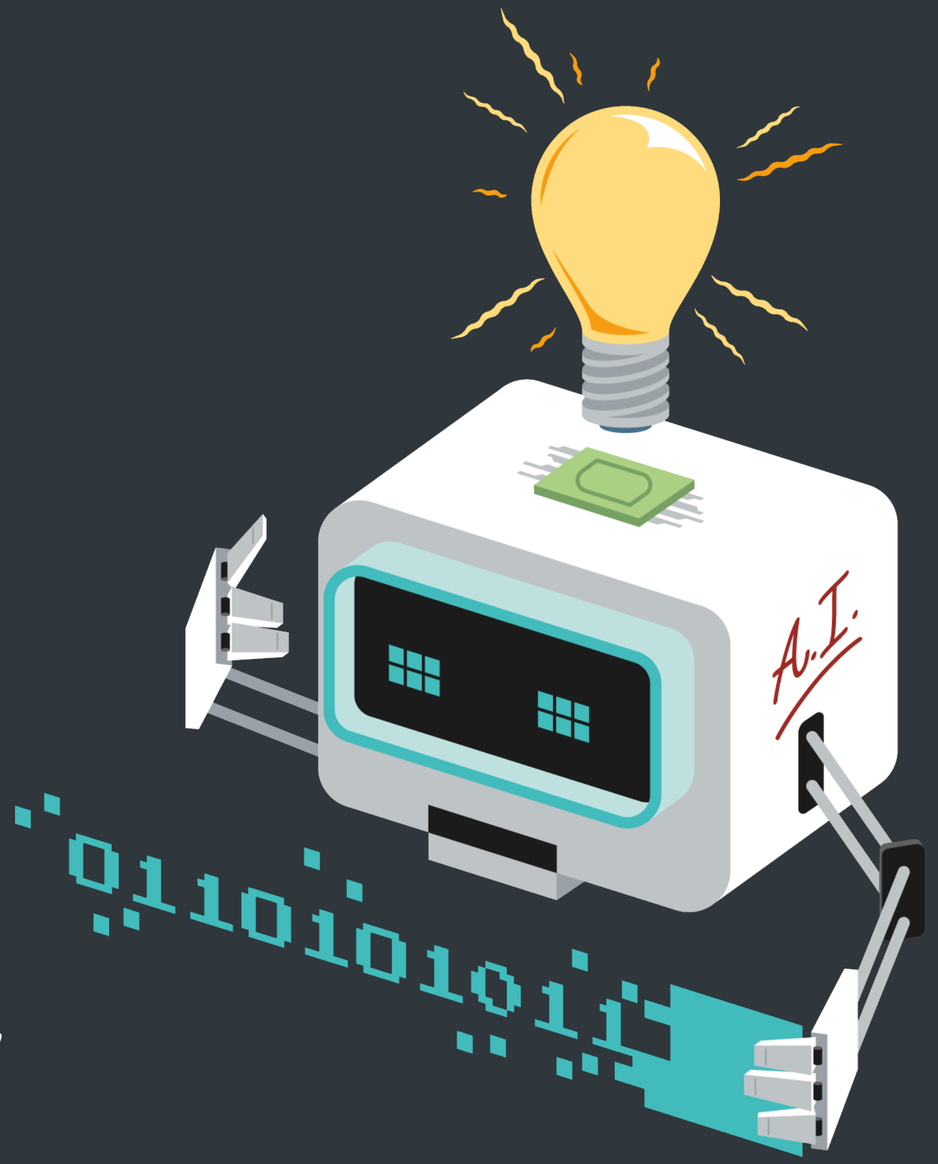
Figure 3: **Table**: Dataset properties. $CV^2 = \mathrm{Var}[z_t]/\mathrm{E}[z_t]^2$ measures burstiness. **(a)**: Sum of weekly P50 point (median) forecast over a one-year prediction range for the different methods (lines) as well as sum of true demand (shaded area), on dataset $\mathcal{I} =$ EC-sub. **(b)**: Weekly P50 risk $R^{0.5}[\mathcal{I}; (7 \cdot k, 7)]$, $k = 0, 1, \ldots,$ for same dataset. **(c)**: Same as (b) for P90 risk.

Take away

Machine learning & AI are transformational.

Wealth of probabilistic machine learning applications.

When deploying machine learning, keep it simple (not simpler).



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Beyza Ermis

Felix Bießmann

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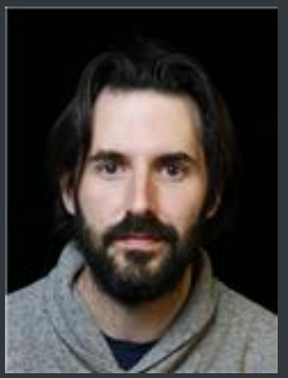
Matthias Seeger

David Salinas

Valentin Flunkert



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