The big picture

target
predictor $p^*$

human
The big picture

target
predictor $p^*$

\textbf{human}

Example:

\begin{verbatim}
y: FEAT FEAT FEAT FEAT FEAT FEAT ...
x: View of Los Gatos Foothills ...

AVAIL AVAIL AVAIL ... SIZE SIZE SIZE SIZE ...

Available July 1 ... 2 bedroom 1 bath ...
\end{verbatim}
The big picture

target predictor $p^*$ → human → information → learning algorithm → learned predictor $\hat{p}$

Example:

$y$: FEAT FEAT FEAT FEAT FEAT ...

$x$: View of Los Gatos Foothills ...

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Example:

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Available July 1 ... 2 bedroom 1 bath ...

Types of information:
Labeled examples (specific) [standard supervised learning]
The big picture

Example:

\[ y: \text{ FEAT FEAT FEAT FEAT FEAT FEAT ... } \]
\[ x: \text{ View of Los Gatos Foothills ... } \]
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Types of information:

- Labeled examples (specific) [standard supervised learning]
- Constraints (general) [Chang, et al., 2007; Druck, et al., 2008]
The big picture

target predictor $p^*$ human information learning algorithm learned predictor $\hat{p}$

Example:

$y$: feat feat feat feat feat ...

$x$: View of Los Gatos Foothills ...

Available July 1 ... 2 bedroom 1 bath ...

Types of information:

Labeled examples (specific) [standard supervised learning]
Constraints (general) [Chang, et al., 2007; Druck, et al., 2008]

Measurements: our unifying framework
The big picture

Example:
\[ y: \text{feat feat feat feat feat ...} \]
\[ x: \text{View of Los Gatos Foothills ...} \]
\[ \text{AVAIL AVAIL AVAIL ... SIZE SIZE SIZE SIZE ...} \]
\[ \text{Available July 1 ... 2 bedroom 1 bath ...} \]

Types of information:
- Labeled examples (specific) [standard supervised learning]
- Constraints (general) [Chang, et al., 2007; Druck, et al., 2008]

Measurements: our unifying framework

Outline:
1. Coherently learn from diverse measurements
The big picture

Target predictor $p^*$ human information learning algorithm learned predictor $\hat{p}$

Example:

$y$: FEAT FEAT FEAT FEAT FEAT FEAT ...

$x$: View of Los Gatos Foothills ...

Available July 1 ... 2 bedroom 1 bath ...

Types of information:

Labeled examples (specific) [standard supervised learning]
Constraints (general) [Chang, et al., 2007; Druck, et al., 2008]

Measurements: our unifying framework

Outline:

1. Coherently learn from diverse measurements
2. Actively select the best measurements
Measurements

$X_1, Y_1$
$X_2, Y_2$
$X_3, Y_3$
...
$X_i, Y_i$
...
$X_n, Y_n$
Measurements

Measurement features: $\sigma(x, y) \in \mathbb{R}^k$

$\sigma( X_1, Y_1 )$
$\sigma( X_2, Y_2 )$
$\sigma( X_3, Y_3 )$
$\vdots \quad \vdots$

$\sigma( X_i, Y_i )$
$\vdots \quad \vdots$

$\sigma( X_n, Y_n )$
Measurements

Measurement features: $\sigma(x, y) \in \mathbb{R}^k$

Measurement values: $\tau \in \mathbb{R}^k$

$$\tau = \sum_{i=1}^{n} \sigma(X_i, Y_i) + \text{noise}$$
Measurements

Measurement features: $\sigma(x, y) \in \mathbb{R}^k$

Measurement values: $\tau \in \mathbb{R}^k$

$$\tau = \sum_{i=1}^{n} \sigma(X_i, Y_i) + \text{noise}$$
Measurements

Measurement features: $\sigma(x, y) \in \mathbb{R}^k$

Measurement values: $\tau \in \mathbb{R}^k$

$$\tau = \sum_{i=1}^{n} \sigma(X_i, Y_i) + \text{noise}$$

Set $\sigma$ to reveal various types of information about $Y$ through $\tau$
Examples of measurements

Fully-labeled example:

\[ \sigma_j(x, y) = \mathbb{I}[x = \text{View of Los ...}, y = * * * * ...] \]
Examples of measurements

Fully-labeled example:

$$\sigma_j(x, y) = \mathbb{I}[x = \text{View of Los ...}, y = * * * * ...]$$

Partially-labeled example:

$$\sigma_j(x, y) = \mathbb{I}[x = \text{View of Los ...}, y_1 = *]$$
Examples of measurements

Fully-labeled example:

$$\sigma_j(x, y) = \mathbb{I}[x = \text{View of Los} \ldots, y = \ast \ast \ast \ast \ldots]$$

Partially-labeled example:

$$\sigma_j(x, y) = \mathbb{I}[x = \text{View of Los} \ldots, y_1 = \ast]$$

Labeled predicate:

$$\sigma_j(x, y) = \sum_i \mathbb{I}[x_i = \text{View}, y_i = \ast]$$
Examples of measurements

Fully-labeled example:
\[ \sigma_j(x, y) = \mathbb{I}[x = \text{View of Los ...}, y = * * * ...] \]

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Label proportions:
\[ \sigma_j(x, y) = \sum_i \mathbb{I}[y_i = *] \]
Examples of measurements

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\[ \sigma_j(x, y) = \mathbb{I}[x = \text{View of Los} \ldots, y = * * * * \ldots] \]

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Labeled predicate:
\[ \sigma_j(x, y) = \sum_i \mathbb{I}[x_i = \text{View}, y_i = *] \]

Label proportions:
\[ \sigma_j(x, y) = \sum_i \mathbb{I}[y_i = *] \]

Label preference:
\[ \sigma_j(x, y) = \sum_i \mathbb{I}[y_i = \text{FEAT}] - \mathbb{I}[y_i = \text{AVAIL}] \]
Examples of measurements

Fully-labeled example:
\[ \sigma_j(x, y) = \mathbb{I}[x = \text{View of Los} \ldots, y = * * * * \ldots] \]

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\[ \sigma_j(x, y) = \sum_i \mathbb{I}[y_i = \text{FEAT}] - \mathbb{I}[y_i = \text{AVAIL}] \]

Can get measurement values \( \tau \) without looking at all examples
Examples of measurements

Fully-labeled example:
\[ \sigma_j(x, y) = \mathbb{I}[x = \text{View of Los} \ldots, y = * * * * \ldots] \]

Partially-labeled example:
\[ \sigma_j(x, y) = \mathbb{I}[x = \text{View of Los} \ldots, y_1 = *] \]

Labeled predicate:
\[ \sigma_j(x, y) = \sum_i \mathbb{I}[x_i = \text{View}, y_i = *] \]

Label proportions:
\[ \sigma_j(x, y) = \sum_i \mathbb{I}[y_i = *] \]

Label preference:
\[ \sigma_j(x, y) = \sum_i \mathbb{I}[y_i = \text{FEAT}] - \mathbb{I}[y_i = \text{AVAIL}] \]

Can get measurement values \( \tau \) without looking at all examples

Next: How to combine these diverse measurements coherently?
Prediction model
Bayesian framework:

\[ X_i \rightarrow Y_i \rightarrow \tau \]
Prediction model

Bayesian framework:
Prediction model

Bayesian framework:

Exponential families:

\[ p_\theta(y \mid x) = \exp\{\langle \phi(x, y), \theta \rangle - A(\theta; x)\} \]
Prediction model

Bayesian framework:

Exponential families:

\[ p_\theta(y \mid x) = \exp\{\langle \phi(x, y), \theta \rangle - A(\theta; x)\} \]

\[ \phi(x, y) \in \mathbb{R}^d: \text{model features} \]
Prediction model

Bayesian framework:

Exponential families:

\[ p_\theta(y \mid x) = \exp\{\langle \phi(x, y), \theta \rangle - A(\theta; x)\} \]

\( \phi(x, y) \in \mathbb{R}^d: \) model features
\( \theta \in \mathbb{R}^d: \) model parameters
Prediction model

Bayesian framework:

Exponential families:

\[ p_\theta(y \mid x) = \exp\{\langle \phi(x, y), \theta \rangle - A(\theta; x)\} \]

\( \phi(x, y) \in \mathbb{R}^d \): model features
\( \theta \in \mathbb{R}^d \): model parameters
\( A(\theta; x) = \int \exp\{\langle \phi(x, y), \theta \rangle\} dy \): log-partition function
Learning via Bayesian inference

Goal: compute $p(\theta, Y | \tau, X)$
Goal: compute \( p(\theta, Y \mid \tau, X) \)

Variational formulation:

\[
\min_{q \in \mathcal{Q}_{Y\theta}} \text{KL} (q(Y, \theta) \mid\mid p(\theta, Y \mid \tau, X))
\]
Learning via Bayesian inference

Goal: compute \( p(\theta, Y \mid \tau, X) \)

Variational formulation:

\[
\min_{q \in Q_{Y\theta}} \text{KL} (q(Y, \theta) \mid\!\mid p(\theta, Y \mid \tau, X))
\]

Approximations:

- \( Q_{Y\theta} \): mean-field factorization of \( q(Y) \) and degenerate \( \tilde{\theta} \)
Learning via Bayesian inference

Goal: compute \( p(\theta, Y \mid \tau, X) \)

Variational formulation:

\[
\min_{q \in Q_{Y\theta}} \text{KL} \, (q(Y, \theta) \| p(\theta, Y \mid \tau, X))
\]

Approximations:

- \( Q_{Y\theta} \): mean-field factorization of \( q(Y) \) and degenerate \( \tilde{\theta} \)
- \( \text{KL} \): measurements only hold in expectation (w.r.t. \( q(Y) \))
Learning via Bayesian inference

Goal: compute \( p(\theta, Y | \tau, X) \)

Variational formulation:
\[
\min_{q \in \mathcal{Q}_{Y\theta}} \text{KL} \left( q(Y, \theta) \| p(\theta, Y | \tau, X) \right)
\]

Approximations:
- \( \mathcal{Q}_{Y\theta} \): mean-field factorization of \( q(Y) \) and degenerate \( \tilde{\theta} \)
- KL: measurements only hold in expectation (w.r.t. \( q(Y) \))

Algorithm:
Apply Fenchel duality → saddlepoint problem
Take alternating stochastic gradient steps
Information geometry viewpoint

(assume zero measurement noise)

\[ \mathcal{P} \overset{\text{def}}{=} \{ p_\theta(y \mid x) : \theta \in \mathbb{R}^d \} \]
Information geometry viewpoint

(assume zero measurement noise)

\( Q \overset{\text{def}}{=} \{ q(y \mid x) : \mathbb{E}_q[\sigma] = \tau \} \)

\( P \overset{\text{def}}{=} \{ p_{\theta}(y \mid x) : \theta \in \mathbb{R}^d \} \)
Information geometry viewpoint
(assume zero measurement noise)

\[ Q \overset{\text{def}}{=} \{ q(y | x) : \mathbb{E}_q[\sigma] = \tau \} \]

\[ P \overset{\text{def}}{=} \{ p_{\theta}(y | x) : \theta \in \mathbb{R}^d \} \]

\[
\min_{q \in Q, p \in P} \text{KL}(q \| p)
\]
Information geometry viewpoint

(assume zero measurement noise)

\[ Q \overset{\text{def}}{=} \{ q(y \mid x) : \mathbb{E}_q[\sigma] = \tau \} \]

\[ P \overset{\text{def}}{=} \{ p_\theta(y \mid x) : \theta \in \mathbb{R}^d \} \]

\[
\min_{q \in Q, p \in P} \text{KL} (q \parallel p)
\]

Interpretation:

Measurements shape \( Q \)       Find model in \( P \) with best fit
Information geometry viewpoint

(assume zero measurement noise)

\[ Q \overset{\text{def}}{=} \{ q(y \mid x) : \mathbb{E}_q[\sigma] = \tau \} \]

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\min_{q \in Q, p \in P} \text{KL}(q \mid\mid p)
\]

Interpretation:

Measurements shape \( Q \) \hspace{1cm} \text{Find model in } P \text{ with best fit}

Two ways to recover supervised learning:

1. Measure \( \sigma = \phi \): \( P \cap Q \) is the unique solution
Information geometry viewpoint

(assume zero measurement noise)

\[ Q \overset{\text{def}}{=} \{ q(y \mid x) : E_q[\sigma] = \tau \} \quad \quad \mathcal{P} \overset{\text{def}}{=} \{ p_\theta(y \mid x) : \theta \in \mathbb{R}^d \} \]

\[
\min_{q \in Q, p \in \mathcal{P}} \text{KL}(q \mid\mid p)
\]

Interpretation:

Measurements shape \( Q \) \quad Find model in \( \mathcal{P} \) with best fit

Two ways to recover supervised learning:

1. Measure \( \sigma = \phi \): \( \mathcal{P} \cap Q \) is the unique solution
2. Measure \( \sigma = \{ \mathbb{I}[x = a, y = b]\} \):
   \( Q = \{ \text{empirical distribution} \} \), project onto \( \mathcal{P} \)
Model features $\phi$ versus measurement features $\sigma$
Model features $\phi$ versus measurement features $\sigma$

Guidelines:
To set $\sigma$, consider human (e.g., full labels)
Model features $\phi$ versus measurement features $\sigma$

Guidelines:

To set $\sigma$, consider human (e.g., full labels)
To set $\phi$, consider statistical generalization (e.g., word suffixes)
Model features $\phi$ versus measurement features $\sigma$

Guidelines:

To set $\sigma$, consider human (e.g., full labels)

To set $\phi$, consider statistical generalization (e.g., word suffixes)

Intuition: consider feature $f(x, y) = \mathbb{I}[x \in A, y = 1]$
Model features $\phi$ versus measurement features $\sigma$

Guidelines:

To set $\sigma$, consider human (e.g., full labels)

To set $\phi$, consider statistical generalization (e.g., word suffixes)

Intuition: consider feature $f(x, y) = \mathbb{I}[x \in A, y = 1]$

If $f$ is a measurement feature (direct):

"inputs in $A$ should be labeled according to $\tau$"
Model features $\phi$ versus measurement features $\sigma$

Guidelines:

To set $\sigma$, consider human (e.g., full labels)
To set $\phi$, consider statistical generalization (e.g., word suffixes)

Intuition: consider feature $f(x, y) = \mathbb{I}[x \in A, y = 1]$

If $f$ is a measurement feature (direct):
“inputs in $A$ should be labeled according to $\tau$”

If $f$ is a model feature (indirect):
“inputs in $A$ should be labeled similarly”
Results on the Craigslist task

\( n = 1000 \) total examples (ads), 11 possible labels

Model:

Conditional random field with standard NLP features
Results on the Craigslist task

$n = 1000$ total examples (ads), 11 possible labels

Model:

Conditional random field with standard NLP features

Measurements:

• fully-labeled examples
• 33 labeled predicates (e.g., $\sum_i \mathbb{I}[x_i = \text{View}, y_i = \text{FEAT}]$)
Results on the Craigslist task

\( n = 1000 \) total examples (ads), 11 possible labels

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- 33 labeled predicates (e.g., \( \sum_i \mathbb{I}[x_i = \text{View}, y_i = \text{FEAT}] \))

Per-position test accuracy (on 100 examples):

<table>
<thead>
<tr>
<th># labeled examples</th>
<th>10</th>
<th>25</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Expectation Criteria</td>
<td>74.6</td>
<td>77.2</td>
<td>80.5</td>
</tr>
<tr>
<td>Constraint-Driven Learning</td>
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<td><strong>81.7</strong></td>
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<tr>
<td>Measurements</td>
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<td>76.5</td>
<td><strong>82.5</strong></td>
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</table>
Results on the Craigslist task

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Per-position test accuracy (on 100 examples):

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Able to integrate labeled examples and predicates gracefully
So far: given measurements, how to learn

Next: how to choose measurements?
Bayesian decision theory

What do we do with an (approximate) posterior \( p(\theta, Y | X, \tau) \)?
What do we do with an (approximate) posterior $p(\theta, Y | X, \tau)$?

Bayes-optimal predictor:

average over $X'$, max over $\hat{Y}'$, average over $Y'$ of reward
Bayesian decision theory

What do we do with an (approximate) posterior $p(\theta, Y | X, \tau)$?

Bayes-optimal predictor:

average over $X'$, max over $\hat{Y}'$, average over $Y'$ of reward $R(\sigma, \tau) = \text{expected reward of Bayes-optimal predictor}$

(i.e., how happy we are with the given situation)
Experimental design (active learning)

Utility of measurement \((\sigma, \tau)\):

\[
U(\sigma, \tau) = R(\sigma, \tau) - C(\sigma)
\]

\(R\) is reward and \(C\) is cost.
Utility of measurement \((\sigma, \tau)\):

\[
U(\sigma, \tau) = R(\sigma, \tau) - C(\sigma)
\]

When considering \(\sigma\), don’t know \(\tau\), so integrate out:

\[
U(\sigma) = E_{p(\tau|X)}[U(\sigma, \tau)]
\]
Experimental design (active learning)

Utility of measurement \((\sigma, \tau)\):

\[
U(\sigma, \tau) = \underbrace{R(\sigma, \tau)}_{\text{reward}} - \underbrace{C(\sigma)}_{\text{cost}}
\]

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Utility of measurement \((\sigma, \tau)\):

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\]

When considering \(\sigma\), don’t know \(\tau\), so integrate out:

\[
U(\sigma) = E_{p(\tau|X)}[U(\sigma, \tau)]
\]

Choose best measurement feature \(\sigma\):

\[
\sigma^* = \arg\max_{\sigma} U(\sigma)
\]
Part-of-speech tagging results

\( n = 1000 \) total examples (sentences), 45 possible labels

**Model**: Indep. logistic regression with standard NLP features
Part-of-speech tagging results

\( n = 1000 \) total examples (sentences), 45 possible labels

Model: Indep. logistic regression with standard NLP features

Measurements:

- fully-labeled examples
- labeled predicates (e.g., \( \sum_i \mathbb{I}[x_i = the, y_i = DT] \))

Use label entropy as surrogate for assessing measurements
Part-of-speech tagging results

\( n = 1000 \) total examples (sentences), 45 possible labels

**Model**: Indep. logistic regression with standard NLP features

**Measurements**:
- fully-labeled examples
- labeled predicates (e.g., \( \sum_i \mathbb{I}[x_i = \text{the}, y_i = \text{DT}] \))

Use label entropy as surrogate for assessing measurements

**Test accuracy** (on 100 examples):

(a) Labeling examples
Part-of-speech tagging results

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Use label entropy as surrogate for assessing measurements

**Test accuracy (on 100 examples):**

(a) Labeling examples

(b) Labeling word types
Part-of-speech tagging results

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Use label entropy as surrogate for assessing measurements

Test accuracy (on 100 examples):

(a) Labeling examples

(b) Labeling word types
Summary

Measurements

target predictor $p^*$ $\xrightarrow{\text{human}}$ measurements $\xrightarrow{\text{learning algorithm}}$ learned predictor $\hat{p}$
Summary

Measurements

Bayesian model

target predictor $p^*$ → human → measurements → learning algorithm → learned predictor $\hat{p}$
Summary

target predictor $p^*$ human → measurements → learning algorithm → learned predictor $\hat{p}$

Measurements

variational approx. → Bayesian model
Summary

target predictor $p^*$ → human measurements → learning algorithm → learned predictor $\hat{p}$

Measurements

variational approx. → Bayesian model

information geometry
Summary

target predictor $p^*$ human $\rightarrow$ measurements $\rightarrow$ learning algorithm $\rightarrow$ learned predictor $\hat{p}$

Measurements

variational approx. $\rightarrow$ Bayesian model $\rightarrow$ decision theory

information geometry
Summary

target predictor $p^*$ → human → measurements → learning algorithm → learned predictor $\hat{p}$

Measurements

- variational approx.
- Bayesian model
- decision theory

information geometry

active learning