Unifying logic and probability
A "New Dawn" for Artificial Intelligence?

Stuart Russell
Computer Science Division, UC Berkeley
LIP6, Université Pierre et Marie Curie
AI: intelligent systems in the real world
AI: intelligent systems in the real world

The world has things in it!!
AI: intelligent systems in the real world

The world has things in it!!

Good Old-Fashioned AI: first-order logic
Why did AI choose first-order logic?

- Provides a *declarative* substrate
  - Learn facts, rules from observation and communication
  - Combine and reuse in arbitrary ways
Why did AI choose first-order logic?

- Provides a **declarative** substrate
  - Learn facts, rules from observation and communication
  - Combine and reuse in arbitrary ways
- **Expressive** enough for **general-purpose** intelligence
  - It provides **concise models**, essential for **learning**
Why did AI choose first-order logic?

- Provides a *declarative* substrate
  - Learn facts, rules from observation and communication
  - Combine and reuse in arbitrary ways
- *Expressive* enough for general-purpose intelligence
  - It provides concise models, essential for learning
  - E.g., rules of chess (32 pieces, 64 squares, ~100 moves)
Why did AI choose first-order logic?

- Provides a **declarative** substrate
  - Learn facts, rules from observation and communication
  - Combine and reuse in arbitrary ways
- **Expressive** enough for general-purpose intelligence
  - It provides concise models, essential for learning
  - E.g., rules of chess (32 pieces, 64 squares, \(~100\) moves)
    - \(~100\) pages as a state-to-state transition matrix (cf HMMs, automata)
    
    R.B.KB.RPPP..PPP..N..N.....PP.....q.pp..Q..n..n..ppp..pppr.b.kb.r
Why did AI choose first-order logic?

- Provides a *declarative* substrate
  - Learn facts, rules from observation and communication
  - Combine and reuse in arbitrary ways

- *Expressive* enough for general-purpose intelligence
  - It provides concise models, essential for learning
  - E.g., rules of chess (32 pieces, 64 squares, ~100 moves)
    - ~100 000 000 000 000 000 000 000 000 000 000 000 000 pages as a state-to-state transition matrix (cf HMMs, automata)
    - *R.B.KB.RPPP..PPP..N..N.....PP....q.pp..Q..n..n..ppp..pppr.b.kb.r*
  - ~100 000 pages in propositional logic (cf circuits, graphical models)
    - *WhiteKingOnC4@Move12*
Why did AI choose first-order logic?

- Provides a *declarative* substrate
  - Learn facts, rules from observation and communication
  - Combine and reuse in arbitrary ways
- *Expressive* enough for general-purpose intelligence
  - It provides concise models, essential for learning
  - E.g., rules of chess (32 pieces, 64 squares, ~100 moves)
    - ~100 000 000 000 000 000 000 000 000 000 000 000 000 pages as a state-to-state transition matrix (cf HMMs, automata)
    
    
    R.B.KB.RPPP..PPP..N..N.....PP....q.pp..Q..n..n..ppp..pppr.b.kb.r
    
    - ~100 000 pages in propositional logic (cf circuits, graphical models)
      
      WhiteKingOnC4@Move12
    
    - 1 page in first-order logic
      
      On(color,piece,x,y,t)
AI: intelligent systems in the real world

The world has things in it!!

Good Old-Fashioned AI: first-order logic
AI: intelligent systems in the real world

Good Old-Fashioned AI: first-order logic
AI: intelligent systems in the real world

The world has things in it!!

The world is uncertain!!

Good Old-Fashioned AI: first-order logic

Modern AI: probabilistic graphical models
Bayesian networks

Define distributions on all possible *propositional* worlds
Bayesian networks

Define distributions on all possible *propositional* worlds

$$P(B, E, A) = P(B) P(E) P(A | B, E)$$
Bayesian networks

Define distributions on all possible *propositional* worlds

\[
P(B,E,A) = P(B) \cdot P(E) \cdot P(A \mid B, E)
\]
Bayesian networks

Define distributions on all possible *propositional* worlds

\[
P(B,E,A) = P(B) \cdot P(E) \cdot P(A | B, E)
\]
Bayesian networks

Define distributions on all possible *propositional* worlds

$$P(B, E, A) = P(B) \cdot P(E) \cdot P(A \mid B, E)$$
AI: intelligent systems in the real world

The world has things in it!!

Good Old-Fashioned AI: first-order logic

Modern AI: probabilistic graphical models

The world is uncertain!!
AI: intelligent systems in the real world

The world has things in it!!

Good Old-Fashioned AI: first-order logic

The world is uncertain!!

Modern AI: probabilistic graphical models

The world is uncertain!!
AI: intelligent systems in the real world

Good Old-Fashioned AI: first-order logic

Modern AI: probabilistic graphical models
AI: intelligent systems in the real world

Good Old-Fashioned AI:
- first-order logic

Modern AI:
- probabilistic graphical models

A New Dawn for AI™:
- first-order probabilistic languages

The world has things in it!!
The world is uncertain!!
“AI is in bloom again … At last, artificial intelligences are thinking along human lines.”
“AI is in bloom again … At last, artificial intelligences are thinking along human lines.”
“AI is in bloom again … At last, artificial intelligences are thinking along human lines.”
“A technique [that] combines the logical underpinnings of the old AI with the power of statistics and probability … is finally starting to disperse the fog of the long AI winter.”
First-order probabilistic languages

- Gaifman [1964]: we can unify logic and probability by defining distributions over possible worlds that are first-order model structures (objects and relations)
First-order probabilistic languages

- Gaifman [1964]: we can unify logic and probability by defining distributions over possible worlds that are *first-order model structures* (objects and relations)
  - Not obvious how to do it – infinitely many parameters??
First-order probabilistic languages

- Gaifman [1964]: we can unify logic and probability by defining distributions over possible worlds that are *first-order model structures* (objects and relations)
  - Not obvious how to do it – infinitely many parameters??
- Simple idea (1990s): combine logical notation for random variables with Bayes net factorization idea
First-order probabilistic languages

- Gaifman [1964]: we can unify logic and probability by defining distributions over possible worlds that are **first-order model structures** (objects and relations)
  - Not obvious how to do it – infinitely many parameters??
- Simple idea (1990s): combine logical notation for random variables with Bayes net factorization idea
Gaifman [1964]: we can unify logic and probability by defining distributions over possible worlds that are **first-order model structures** (objects and relations)
- Not obvious how to do it – infinitely many parameters??
- Simple idea (1990s): combine logical notation for random variables with Bayes net factorization idea
First-order probabilistic languages

- Gaifman [1964]: we can unify logic and probability by defining distributions over possible worlds that are **first-order model structures** (objects and relations)
  - Not obvious how to do it – infinitely many parameters??
- Simple idea (1990s): combine logical notation for random variables with Bayes net factorization idea
First-order probabilistic languages

- Gaifman [1964]: we can unify logic and probability by defining distributions over possible worlds that are **first-order model structures** (objects and relations)
  - Not obvious how to do it – infinitely many parameters??
- Simple idea (1990s): combine logical notation for random variables with Bayes net factorization idea
An important distinction in logic

- **Closed-universe** languages assume unique names and domain closure, i.e., known objects
  - Like Prolog, databases (Herbrand semantics)
  - Poole 93, Sato 97, Koller & Pfeffer 98, De Raedt 00, etc.

- **Open-universe** languages allow uncertainty over the existence and identity of objects
  - Like full first-order logic
  - BLOG (Milch & Russell 05): declarative OUPM language
  - Probabilistic programming (Pfeffer 03, Goodman et al 08): distribution on execution traces of stochastic programs
Closed vs open universes

Given

Bill = Father(William) and Bill = Father(Junior)

How many children does Bill have?
Closed vs open universes

Given
Bill = Father(William) and Bill = Father(Junior)
How many children does Bill have?

Closed-universe (Herbrand) semantics:
2
Given
Bill = Father(William) and Bill = Father(Junior)
How many children does Bill have?

Closed-universe (Herbrand) semantics:
2
Open-universe (full first-order) semantics:
Between 1 and $\infty$
AI: intelligent systems in the real world

The world has things in it and we don’t know what they are!!

A New Dawn for AI™: first-order probabilistic languages
Key idea

- **Given:**
  - An open-universe probability model
  - Evidence from observations
- **Apply:** Bayesian updating
- **Output:** beliefs about what objects exist, their identities, and their interrelations
Open-universe semantics

Possible worlds for a language with two constant symbols A and B and one relation symbol.

Closed-universe semantics

Open-universe semantics
Open-universe semantics

Possible worlds for a language with two constant symbols A and B and one relation symbol

Closed-universe semantics

Open-universe semantics

but how can we define \( P \) on \( \Omega \) ??
Bayes nets build propositional worlds

- Burglary
- Earthquake
- Alarm
Bayes nets build propositional worlds

- Burglary
- Earthquake
- Alarm

Burglary
Bayes nets build propositional worlds

Burglary
Earthquake
Alarm

Burglary
not Earthquake
Bayes nets build propositional worlds

Burglary
not Earthquake
Alarm
Open-universe models in BLOG

- Construct worlds using two kinds of steps, proceeding in topological order:
  - **Dependency statements**: Set the value of a function or relation on a tuple of (quantified) arguments, conditioned on parent values
    - Alarm(h) \sim \text{CPT[..]}(\text{Burglary}(h), \text{Earthquake}(\text{Region}(h)))
Open-universe models in BLOG

▪ Construct worlds using two kinds of steps, proceeding in topological order:
  ▪ **Dependency statements**: Set the value of a function or relation on a tuple of (quantified) arguments, conditioned on parent values
    ▪ Alarm(h) ~ CPT[..](Burglary(h), Earthquake(Region(h)))
  ▪ **Number statements**: Add some objects to the world, conditioned on what objects and relations exist so far
    ▪ #GeologicalFaultRegions ~ Uniform{1…10}
Example: Multi-target tracking on radar
Example: Multi-target tracking on radar
Example: Multi-target tracking on radar
Example: Multi-target tracking on radar
Example: Multi-target tracking on radar

- Track termination
- False alarm
- Detection failure
- Track initiation
#Aircraft(EntryTime = t) ~ Poisson[\lambda_a]()

Exits(a,t)
    if InFlight(a,t) then ~ Boolean[\alpha_e]()

InFlight(a,t)
    if t < EntryTime(a) then = false
    elseif t = EntryTime(a) then = true
    else = (InFlight(a,t-1) & !Exits(a,t-1));

X(a,t)
    if t = EntryTime(a) then ~ InitState()
    elseif InFlight(a,t) then
        ~ Normal[F*X(a,t-1),\Sigma_x]()

#Blip(Source=a, Time=t)
    if InFlight(a,t) then
        ~ Bernoulli[DetectionProbability(X(a,t))]();

#Blip(Time=t) ~ Poisson[\lambda_f]()

Z(b)
    if Source(b)=null then ~ Uniform[R]()
    else ~ Normal[H*X(Source(b),Time(b)),\Sigma_z]()
#Aircraft(EntryTime = t) ~ Poisson[λ_a]()

Exits(a,t)
    if InFlight(a,t) then ~ Boolean[α_e]()

InFlight(a,t)
    if t < EntryTime(a) then = false
    elseif t = EntryTime(a) then = true
    else = (InFlight(a,t-1) & !Exits(a,t-1));

X(a,t)
    if t = EntryTime(a) then ~ InitState()
    elseif InFlight(a, t) then
        ~ Normal[F*X(a,t-1),Σ_x]()

#Blip(Source=a, Time=t)
    if InFlight(a,t) then
        ~ Bernoulli[DetectionProbability(X(a,t))]();

#Blip(Time=t) ~ Poisson[λ_f]()

Z(b)
    if Source(b)=null then ~ Uniform[R]()
    else ~ Normal[H*X(Source(b),Time(b)),Σ_z]()
# Aircraft (EntryTime = t) ~ Poisson[λ_a]()

Exits(a,t)
  if InFlight(a,t) then ~ Boolean[α_e]()

InFlight(a,t)
  if t < EntryTime(a) then = false
  elseif t = EntryTime(a) then = true
  else = (InFlight(a,t-1) & !Exits(a,t-1));

X(a,t)
  if t = EntryTime(a) then ~ InitState()
  elseif InFlight(a,t) then ~ Normal[F*X(a,t-1),Σ_x]()

# Blip(Source=a, Time=t)
  if InFlight(a,t) then ~ Bernoulli[DetectionProbability(X(a,t))]()

# Blip(Time=t) ~ Poisson[λ_f]()

Z(b)
  if Source(b)=null then ~ Uniform[R]()
  else ~ Normal[H*X(Source(b),Time(b)),Σ_z]()
#Aircraft(EntryTime = t) ~ Poisson[λ_a]()

Exits(a,t)
    if InFlight(a,t) then ~ Boolean[α_e]()

InFlight(a,t)
    if t < EntryTime(a) then = false
    elseif t = EntryTime(a) then = true
    else = (InFlight(a,t-1) & !Exits(a,t-1));

X(a,t)
    if t = EntryTime(a) then ~ InitState()
    elseif InFlight(a,t) then
        ~ Normal[F*X(a,t-1),Σ_x]();

#Blip(Source=a, Time=t)
    if InFlight(a,t) then
        ~ Bernoulli[DetectionProbability(X(a,t))]();
    ~ Poisson[λ_f]();

    if Source(b)=null then ~ Uniform[R]()
    else ~ Normal[H*X(Source(b),Time(b)),Σ_z]();
Objects are defined by type, origin, number:
- \(<\text{Aircraft},<\text{EntryTime},<\text{TimeStep,5}>>,2>\)
- \(<\text{Blip},<\text{Source}, <\text{Aircraft},<\text{EntryTime},<\text{TimeStep,5}>>,2>,<\text{Time},<\text{TimeStep,7}>>,1>\)

Each basic random variable is a function or predicate symbol indexed by a tuple of objects:
- \(\text{InFlight}<\text{Aircraft},<\text{EntryTime},<\text{TimeStep,5}>>,2>,<\text{TimeStep,7}>(\omega)\)

Each possible world \(\omega\) specifies values for all number variables and basic random variables

Probability of \(\omega\) is given by the product of conditional probabilities specified in the model
Semantics

Every well-formed* BLOG model specifies a unique proper probability distribution over all possible worlds definable given its vocabulary.

* No infinite receding ancestor chains, no conditioned cycles, all expressions finitely evaluable
BLOG Example Library

1. PCFG for simple English
2. Simplified 3D vision
3. Hurricane prediction
4. Burglary
5. Balls and urns (counting)
6. Sybil attack (cybersecurity)
7. Students and grades
8. Topic models (LDA)
9. Citation information extraction
10. Competing workshops
11. Galaxy model
12. Infinite mixture of Gaussians
13. Monopoly (invisible opponent)
14. Blackjack
15. Multi-target tracking
16. HMM for genetic sequences
17. Weather forecasting
18. Video background subtraction
19. Financial volatility
20. Autoregression time series
21. Kalman filter
22. Infinite-state HMM
BLOG Example Library

1. PCFG for simple English
2. Simplified 3D vision
3. Hurricane prediction
4. Burglary
5. Balls and urns (counting)
6. Sybil attack (cybersecurity)
7. Students and grades
8. Topic models (LDA)
9. Citation information extraction
10. Competing workshops
11. Galaxy model
12. Infinite mixture of Gaussians
13. Monopoly (invisible opponent)
14. Blackjack
15. Multi-target tracking
16. HMM for genetic sequences
17. Weather forecasting
18. Video background subtraction
19. Financial volatility
20. Autoregression time series
21. Kalman filter
22. Infinite-state HMM
BLOG Example Library

1. PCFG for simple English
2. Simplified 3D vision
3. Hurricane prediction
4. Burglary
5. Balls and urns (counting)
6. Sybil attack (cybersecurity)
7. Students and grades
8. Topic models (LDA)
9. Citation information extraction
10. Competing workshops
11. Galaxy model
12. Infinite mixture of Gaussians
13. Monopoly (invisible opponent)
14. Blackjack
15. Multi-target tracking
16. HMM for genetic sequences
17. Weather forecasting
18. Video background subtraction
19. Financial volatility
20. Autoregression time series
21. Kalman filter
22. Infinite-state HMM
Citation information extraction

- **Given:** a set of text strings from reference lists:

- **Decide:**
  - What papers exist
  - Their titles and authors
  - For each paper, the papers it cites
#Researcher ~ NumResearchersPrior();

Name(r) ~ NamePrior();

#Paper(FirstAuthor = r) ~
    NumPapersPrior(Position(r));

Title(p) ~ TitlePrior();

PubCited(c) ~ Uniform({Paper p});

Text(c) ~ NoisyCitationGrammar
    (Name(FirstAuthor(PubCited(c))),
    Title(PubCited(c)));
(Simplified) BLOG model

#Researcher ~ NumResearchersPrior();

Name(r) ~ NamePrior();

#Paper(FirstAuthor = r) ~
    NumPapersPrior(Position(r));

Title(p) ~ TitlePrior();

PubCited(c) ~ Uniform({Paper p});

Text(c) ~ NoisyCitationGrammar
    (Name(FirstAuthor(PubCited(c))),
     Title(PubCited(c)));
(Simplified) BLOG model

#Researcher ~ NumResearchersPrior();
Name(r) ~ NamePrior();

#Paper(FirstAuthor = r) ~
   NumPapersPrior(Position(r));

Title(p) ~ TitlePrior();

PubCited(c) ~ Uniform({Paper p});

Text(c) ~ NoisyCitationGrammar
   (Name(FirstAuthor(PubCited(c))), Title(PubCited(c)));
Four data sets of ~300-500 citations, referring to ~150-300 papers
Fraction of citation clusters imperfectly recovered

Four data sets of ~300-500 citations, referring to ~150-300 papers
1. PCFG for simple English
2. Simplified 3D vision
3. Hurricane prediction
4. Burglary
5. Balls and urns (counting)
6. Sybil attack (cybersecurity)
7. Students and grades
8. Topic models (LDA)
9. Citation information extraction
10. Competing workshops
11. Galaxy model
12. Infinite mixture of Gaussians
13. Monopoly (invisible opponent)
14. Blackjack
15. Multi-target tracking
16. HMM for genetic sequences
17. Weather forecasting
18. Video background subtraction
19. Financial volatility
20. Autoregression time series
21. Kalman filter
22. Infinite-state HMM
BLOG Example Library

1. PCFG for simple English
2. Simplified 3D vision
3. Hurricane prediction
4. Burglary
5. Balls and urns (counting)
6. Sybil attack (cybersecurity)
7. Students and grades
8. Topic models (LDA)
9. Citation information extraction
10. Competing workshops
11. Galaxy model
12. Infinite mixture of Gaussians
13. Monopoly (invisible opponent)
14. Blackjack
15. Multi-target tracking
16. HMM for genetic sequences
17. Weather forecasting
18. Video background subtraction
19. Financial volatility
20. Autoregression time series
21. Kalman filter
22. Infinite-state HMM
Theorem: BLOG inference algorithms (rejection sampling, importance sampling, MCMC) converge* to correct posteriors for any well-formed model, for any finitely evaluable first-order query.

Algorithms dynamically construct finite partial worlds with ground-atom variables directly relevant to query and evidence.
MCMC on values
MCMC on values

Earthquake(R_a)

Earthquake(R_b)

B(H_1)

B(H_2)

B(H_3)

A(H_1)

A(H_2)

A(H_3)

Earthquake(R_a)

Earthquake(R_b)

B(H_1)

B(H_2)

B(H_3)

A(H_1)

A(H_2)

A(H_3)

Earthquake(R_a)

Earthquake(R_b)

B(H_1)

B(H_2)

B(H_3)

A(H_1)

A(H_2)

A(H_3)

Earthquake(R_a)

Earthquake(R_b)

B(H_1)

B(H_2)

B(H_3)

A(H_1)

A(H_2)

A(H_3)
MCMC on values

Earthquake(R_a)

B(H_1)
A(H_1)

B(H_2)
A(H_2)

B(H_3)
A(H_3)

B(H_4)
A(H_4)

B(H_5)
A(H_5)

Earthquake(R_b)

B(H_1)
A(H_1)

B(H_2)
A(H_2)

B(H_3)
A(H_3)

B(H_4)
A(H_4)

B(H_5)
A(H_5)
MCMC on values
MCMC on values
Inference

- Efficient inference is the bottleneck
  - Real-world applications use special-purpose inference
- A substantial engineering problem
  - Modular design with “plug-in” expert samplers
  - Optimizing compiler technology to reduce overhead
  - Data and process parallelism
  - Incremental query evaluation (cf database systems)
Application: CTBT

- Bans testing of nuclear weapons on earth
  - Allows outside inspection of 1000km\(^2\) (18km radius)
- 183/195 states have signed
- 158/195 have ratified
- Need 8 more ratifications including US, China
- US Senate refused to ratify in 1998
  - “too hard to monitor”
Application: CTBT

- Bans testing of nuclear weapons on earth
  - Allows outside inspection of 1000km² (18km radius)
- 183/195 states have signed (including France)
- 158/195 have ratified
- Need 8 more ratifications including US, China
- US Senate refused to ratify in 1998
  - “too hard to monitor”
Application: CTBT

- Bans testing of nuclear weapons on earth
  - Allows outside inspection of 1000km\(^2\) (18km radius)
- 183/195 states have signed (including France)
- 158/195 have ratified (including France)
- Need 8 more ratifications including US, China
- US Senate refused to ratify in 1998
  - “too hard to monitor”
2053 nuclear explosions, 300K deaths
Global seismic monitoring

- **Given**: continuous waveform measurements from a global network of seismometer stations
- **Output**: a *bulletin* listing seismic *events*, with
  - Time
  - Location (*latitude*, *longitude*)
  - Depth
  - Magnitude
Why is this a hard problem?

- ~10 000 “detections” per day, 90% false
- Signals take 15 minutes to several hours to traverse the earth, so they are all mixed up
- CTBTO system ($GA \rightarrow SEL3$) developed over 10 years, $100M$ software plus $1B$ network
  - Finds 69% of significant events plus about twice as many spurious (nonexistent) events
  - 16 human analysts correct or discard SEL3 events, create new events, generate LEB (“ground truth”)
  - Unreliable below magnitude 4 (1kT)
Very short course in seismology
Local spike in signal value; attributes are:

- Onset time*
- Amplitude*
- Azimuth* and slowness* (= direction it arrives from)
- Phase* (= one of 14 distinct wave types: P, S, etc.)
Open-universe model

- Created a BLOG model describing
  - Event occurrence
  - Signal propagation
  - Signal detection probability
  - Measurement uncertainty
  - Noise processes producing false detections
- Wrote a fast inference algorithm for this model
- \(\Rightarrow\) **NET-VISA** (network vertically integrated seismic analysis)
#SeismicEvents ~ Poisson[T*λ_e];

_Time(e) ~ Uniform(0,T)_

_IsEarthQuake(e) ~ Bernoulli(.999);_

_Location(e) ~ if(IsEarthQuake(e)) then SpatialPrior() else UniformEarthDistribution();_

_Depth(e) ~ if(IsEarthQuake(e)) then Uniform[0,700] else 0;_

_Magnitude(e) ~ Exponential(log(10));_

_IsDetected(e,p,s) ~ Logistic[weights(s,p)](Magnitude(e), Depth(e), Distance(e,s));_

_Detections(site = s) ~ Poisson[T*λ_f(s)];_

_Detections(event=e, phase=p, station=s) = if(IsDetected(e,p,s)) then 1 else 0;_

_OnsetTime(a,s) ~ if (event(a) = null) then Uniform[0,T] else Time(event(a)) + GeoTravelTime(Distance(event(a),s),Depth(event(a)),phase(a)) + Laplace(μ_t(s), σ_t(s))_

_Amplitude(a,s) ~ If (event(a) = null) then NoiseAmplitudeDistribution(s) else AmplitudeModel(Magnitude(event(a)), Distance(event(a),s),Depth(event(a)),phase(a))_

_Azimuth(a,s) ~ If (event(a) = null) then Uniform(0, 360) else GeoAzimuth(Location(event(a)),Depth(event(a)),phase(a),Site(s)) + Laplace(0,σ_a(s))_

_Slowness(a,s) ~ If (event(a) = null) then Uniform(0,20) else GeoSlowness(Location(event(a)),Depth(event(a)),phase(a),Site(s)) + Laplace(0,σ_a(s))_

_ObservedPhase(a,s) ~ CategoricalPhaseModel(phase(a))_
# Seismic Events

\[ \#\text{SeismicEvents} \sim \text{Poisson}[T\*\lambda_e]; \]

\[ \text{Time}(e) \sim \text{Uniform}(0,T) \]

\[ \text{IsEarthQuake}(e) \sim \text{Bernoulli}(0.999); \]

\[ \text{Location}(e) \sim \text{if IsEarthQuake}(e) \text{ then SpatialPrior()} \text{ else UniformEarthDistribution();} \]

\[ \text{Depth}(e) \sim \text{if IsEarthQuake}(e) \text{ then Uniform}[0,700] \text{ else 0;} \]

\[ \text{Magnitude}(e) \sim \text{Exponential}(\log(10)); \]

\[ \text{IsDetected}(e,p,s) \sim \text{Logistic}[\text{weights}(s,p)](\text{Magnitude}(e), \text{Depth}(e), \text{Distance}(e,s)); \]

\[ \#\text{Detections(site = s)} \sim \text{Poisson}[T\*\lambda_f(s)]; \]

\[ \#\text{Detections(event=e, phase=p, station=s)} = \text{if IsDetected(e,p,s) then 1 else 0}; \]

\[ \text{OnsetTime}(a,s) \sim \text{if (event(a) = null) then Uniform}[0,T] \text{ else} \]

\[ \quad \text{Time(event(a))} + \text{GeoTravelTime(Distance(event(a),s),Depth(event(a)),phase(a))} \]

\[ \quad + \text{Laplace}(\mu_t(s), \sigma_t(s)) \]

\[ \text{Amplitude}(a,s) \sim \text{if (event(a) = null) then NoiseAmplitudeDistribution(s)} \]

\[ \quad \text{else AmplitudeModel(Magnitude(event(a)), Distance(event(a),s),Depth(event(a)),phase(a))} \]

\[ \text{Azimuth}(a,s) \sim \text{if (event(a) = null) then Uniform}(0, 360) \]

\[ \quad \text{else GeoAzimuth(Location(event(a)),Depth(event(a)),phase(a),Site(s))} + \text{Laplace}(0,\sigma_a(s)) \]

\[ \text{Slowness}(a,s) \sim \text{if (event(a) = null) then Uniform}(0,20) \]

\[ \quad \text{else GeoSlowness(Location(event(a)),Depth(event(a)),phase(a),Site(s))} + \text{Laplace}(0,\sigma_a(s)) \]

\[ \text{ObservedPhase}(a,s) \sim \text{CategoricalPhaseModel(phase(a))} \]
#SeismicEvents ~ Poisson[T*λ_e];

Time(e) ~ Uniform(0,T)

IsEarthQuake(e) ~ Bernoulli(.999);

Location(e) ~ if IsEarthQuake(e) then SpatialPrior() else UniformEarthDistribution();

Depth(e) ~ if IsEarthQuake(e) then Uniform[0,700] else 0;

Magnitude(e) ~ Exponential(log(10));

IsDetected(e,p,s) ~ Logistic[weights(s,p)](Magnitude(e), Depth(e), Distance(e,s));

#Detections(site = s) ~ Poisson[T*λ_f(s)];

#Detections(event=e, phase=p, station=s) = if IsDetected(e,p,s) then 1 else 0;

OnsetTime(a,s) ~ if (event(a) = null) then Uniform[0,T] else
    Time(event(a)) + GeoTravelTime(Distance(event(a),s),Depth(event(a)),phase(a))
    + Laplace(μ_t(s), σ_t(s))

Amplitude(a,s) ~ If (event(a) = null) then NoiseAmplitudeDistribution(s)
    else AmplitudeModel(Magnitude(event(a)), Distance(event(a),s),Depth(event(a)),phase(a))

Azimuth(a,s) ~ If (event(a) = null) then Uniform(0,360)
    else GeoAzimuth(Location(event(a)),Depth(event(a)),phase(a),Site(s)) + Laplace(0,σ_a(s))

Slowness(a,s) ~ If (event(a) = null) then Uniform(0,20)
    else GeoSlowness(Location(event(a)),Depth(event(a)),phase(a),Site(s)) + Laplace(0,σ_a(s))

ObservedPhase(a,s) ~ CategoricalPhaseModel(phase(a))
Estimating the location prior

- Kernel density estimate plus uniform component:

\[ P_{\theta,1}(e_t) = 0.01 \frac{1}{4\pi R^2} + 0.999 \frac{1}{H} \sum_{h=1}^{H} K_{b,\theta_h}(e_t) \]

\[ K_{b,\pi}(y) = \frac{1 + 1/b^2}{2\pi R^2} \frac{\exp(-\Delta_{xy}/b)}{1 + \exp(-\pi/b)} \]

- Kernel width \( b \) estimated by LOOCV:
Event location prior
#SeismicEvents ~ Poisson[T*λ_e];

Time(e) ~ Uniform(0,T)

IsEarthQuake(e) ~ Bernoulli(.999);

Location(e) ~ if IsEarthQuake(e) then SpatialPrior() else UniformEarthDistribution();

Depth(e) ~ if IsEarthQuake(e) then Uniform[0,700] else 0;

Magnitude(e) ~ Exponential(log(10));

IsDetected(e,p,s) ~ Logistic[weights(s,p)](Magnitude(e), Depth(e), Distance(e,s));

#Detections(site = s) ~ Poisson[T*λ_f(s)];

#Detections(event=e, phase=p, station=s) = if IsDetected(e,p,s) then 1 else 0;

OnsetTime(a,s) ~ if (event(a) = null) then Uniform[0,T] else
  Time(event(a)) + GeoTravelTime(Distance(event(a),s),Depth(event(a)),phase(a))
  + Laplace(μ_t(s), σ_t(s))

Amplitude(a,s) ~ If (event(a) = null) then NoiseAmplitudeDistribution(s)
  else AmplitudeModel(Magnitude(event(a)), Distance(event(a),s),Depth(event(a)),phase(a))

Azimuth(a,s) ~ If (event(a) = null) then Uniform(0, 360)
  else GeoAzimuth(Location(event(a)),Depth(event(a)),phase(a),Site(s)) + Laplace(0,σ_a(s))

Slowness(a,s) ~ If (event(a) = null) then Uniform(0,20)
  else GeoSlowness(Location(event(a)),Depth(event(a)),phase(a),Site(s)) + Laplace(0,σ_a(s))

ObservedPhase(a,s) ~ CategoricalPhaseModel(phase(a))
Detection probability as a function of distance (station 6, $m_b$ 3.5)

P phase  

S phase
#SeismicEvents \sim Poisson[T^*\lambda_e];

\textit{Time}(e) \sim Uniform(0,T)

\textit{IsEarthQuake}(e) \sim Bernoulli(.999);

\textit{Location}(e) \sim \text{if IsEarthQuake}(e) \text{ then SpatialPrior() else UniformEarthDistribution();}

\textit{Depth}(e) \sim \text{if IsEarthQuake}(e) \text{ then Uniform}[0,700] \text{ else 0;}

\textit{Magnitude}(e) \sim \text{Exponential}(\log(10));

\textit{IsDetected}(e,p,s) \sim \text{Logistic}[weights(s,p)](\textit{Magnitude}(e), \textit{Depth}(e), \textit{Distance}(e,s));

\#\textit{Detections}(site = s) \sim \text{Poisson}[T^*\lambda_f(s)];

\#\textit{Detections}(event=e, phase=p, station=s) = \text{if IsDetected}(e,p,s) \text{ then 1 else 0;}

\textit{OnsetTime}(a,s) \sim \text{if (event(a) = null) then Uniform}[0,T] \text{ else }

\quad \text{Time(event(a))} + \text{GeoTravelTime(Distance(event(a),s),Depth(event(a)),phase(a))}

\quad + \text{Laplace}(\mu_t(s), \sigma_t(s))

\textit{Amplitude}(a,s) \sim \text{if (event(a) = null) then NoiseAmplitudeDistribution(s) else AmplitudeModel(Magnitude(event(a)), Distance(event(a),s),Depth(event(a)),phase(a))}

\textit{Azimuth}(a,s) \sim \text{if (event(a) = null) then Uniform}(0, 360)

\quad \text{else GeoAzimuth(Location(event(a)),Depth(event(a)),phase(a),Site(s))} + \text{Laplace}(0, \sigma_a(s))

\textit{Slowness}(a,s) \sim \text{if (event(a) = null) then Uniform}(0,20)

\quad \text{else GeoSlowness(Location(event(a)),Depth(event(a)),phase(a),Site(s))} + \text{Laplace}(0, \sigma_a(s))

\textit{ObservedPhase}(a,s) \sim \text{CategoricalPhaseModel(phase(a))}
Travel-time residual (station 6)
Evaluation

- 11 weeks of training data, April 6 – June 20, 2009
- 1 week of validation data, March 22-29, 2009
  - 832 LEB events
- Evaluated existing UN automated system (GA) and NET-VISA using LEB as “ground truth”
Fraction of events missed

Existing UN system

<table>
<thead>
<tr>
<th>Magnitude</th>
<th>ALL</th>
<th>0--2</th>
<th>2--3</th>
<th>3--4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>30</td>
<td>35</td>
<td>45</td>
<td>30</td>
</tr>
</tbody>
</table>
Fraction of events missed

Existing UN system
NET-VISA
Event distribution: LEB vs SEL3

LEB(yellow) and SEL3(red)
Event distribution: LEB vs NET-VISA
Detecting Events Found by Regional Networks

- Continental US (33 Events)
- Japan (1565 Events)
- Europe (101 Events)
- Central Asia (101 Events)

LEB Recall
NET-VISA Recall
NEIC Event not in LEB
North Korea event of 5/25/09

Number of associated detections for event:
- SEL3: 39
- NET-VISA: 53
- LEB: 53

50 of 53 detections in common between LEB and NET-VISA;
LEB added 8 by hand.

Separate training set 1/4/08-1/4/09
Test set 1/5/09-1/26/09
Concluding remarks

- AI, control theory, operations research, and statistics tried and failed to find common ground in the 1950s
Concluding remarks

- AI, control theory, operations research, and statistics tried and failed to find common ground in the 1950s
  - They had no common mathematical formalism!
Concluding remarks

- AI, control theory, operations research, and statistics tried and failed to find common ground in the 1950s
  - They had no common mathematical formalism!
- Robotics and vision separated from AI in the 1970s and 1980s for similar reasons
Concluding remarks

- AI, control theory, operations research, and statistics tried and failed to find common ground in the 1950s
  - They had no common mathematical formalism!
- Robotics and vision separated from AI in the 1970s and 1980s for similar reasons
- Bayesian networks and statistical machine learning helped to reintegrate some of these fields in the 1990s
Concluding remarks

- AI, control theory, operations research, and statistics tried and failed to find common ground in the 1950s
  - They had no common mathematical formalism!
- Robotics and vision separated from AI in the 1970s and 1980s for similar reasons
- Bayesian networks and statistical machine learning helped to reintegrate some of these fields in the 1990s
- Unifying logic and probability may help us to
  - complete the reintegration of reasoning, planning, perception, and language understanding
  - find the light at the end of the tunnel
Merci pour votre attention!

L'orateur est soutenu par, et cette présentation est donnée sous les auspices de, la Chaire Internationale de Recherche Blaise Pascal financée par l'État et la Région Île de France, gérée par la Fondation de l'École Normale Supérieure.

Joint work with Brian Milch, David Sontag, Andrey Kolo bov, Bhaskara Marthi, Lei Li, Siddharth Srivastava, Nimar Arora, Erik Sudderth, Paul Kidwell, David Moore, Kevin Mayeda, Steve Myers, Christopher Lin, Tony Dear, Ron Sun, Min Joon Seo

+ help from Ola Dahlman, Ronan LeBras, Lassina Zerbo, Sheila Vaidya, Bob Engdahl, Barbara Romanowicz, Jeff Given, Spilio Spiliopoulos, Elena Tomuta

Research funded by DARPA, CTBTO, and DTRA

Questions?