High-Power Logical Representation via Rulelog for Neuro-Symbolic *(position paper)*

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Coherent Knowledge**

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Outline

- Why to combine KRR (symbolic) + ML (incl. neuro)
  - Esp. from viewpoint of ML
- KRR requirements for combining w/ ML
  - Expressiveness, scalability
- Rulelog KRR as a candidate for such combination
  - Features, Ergo implementation, applications. Pros/cons.
- Directions for future research

The Core of AI

Artificial Intelligence (AI)

Machine Learning (ML)

Knowledge Representation and Reasoning (KRR)

KRR is required for Cognitive Computing too.

Logic-based KRR's Roles in AI

- Complements ML … in sense of induction from data
  … to enable ML in broader sense
- The power of cultural transmission
  - "Evolution's lesson" (Wolfgang Bibel)
- Accumulate knowledge coherently
- Communicate with humans: expertise, questions
- "Inject" ML results into predictable software

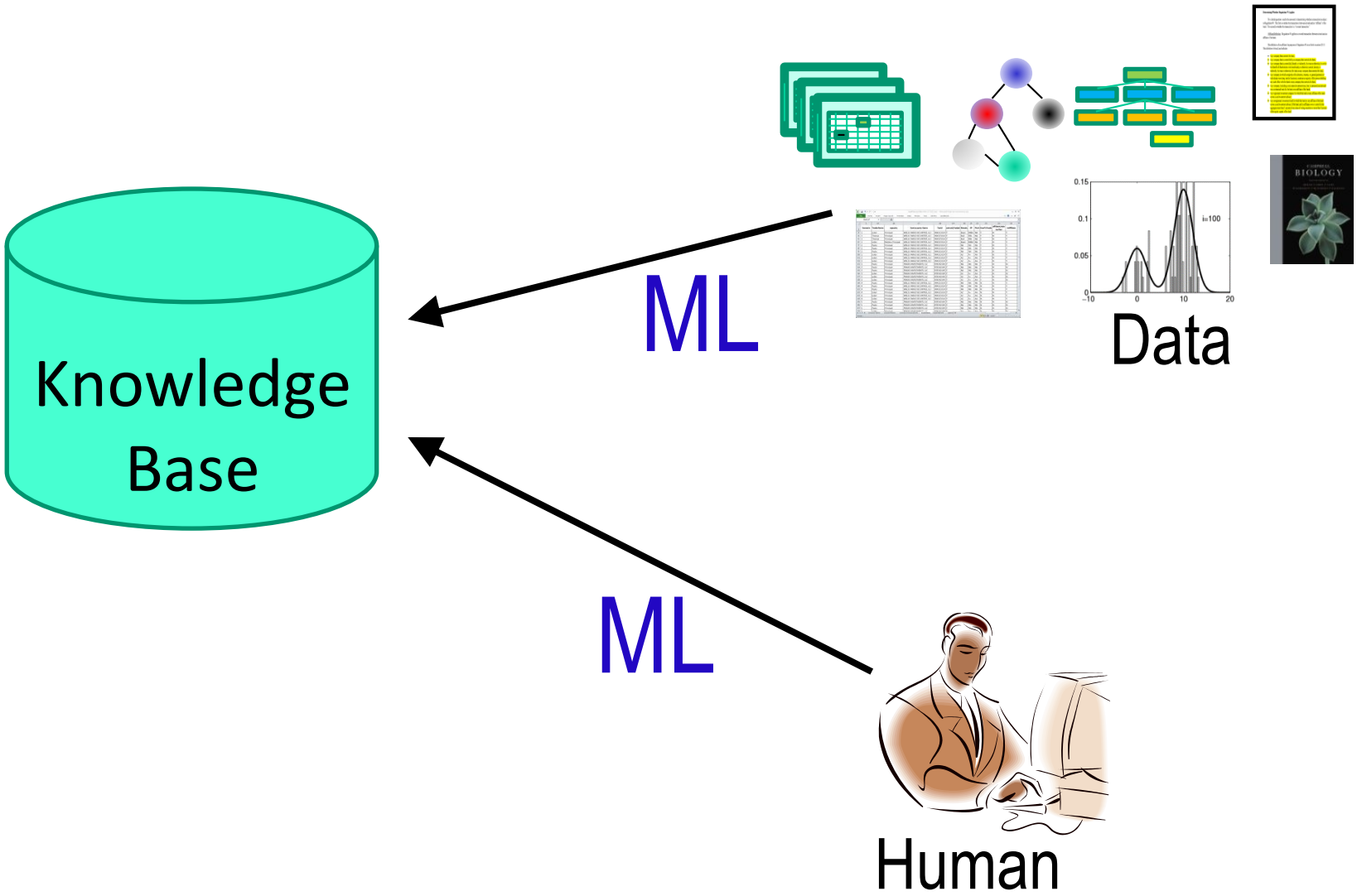
Why Combine ML with KRR

2 ways it's useful or even required,
from the viewpoint of KRR, i.e., "for KRR's sake":

1. KB construction: ML is useful to *supply* knowledge

2. *Improve the process of knowledge acquisition*
   - (Can view this as supplying a kind of meta-knowledge)
   - From manual entry of knowledge, e.g., encoding NL into rules
   - From knowledge interchange

Why Combine ML with KRR – diagram



Why Combine KRR with ML (I)

10 ways it's useful or even required,
from the viewpoint of ML, i.e., "for ML's sake":

1. The *prediction* step of ML requires reasoning
   - This could be pulled by an ML system via backchaining
   - Why not hook up various external programs such as reasoners, to NNs to evaluate some nodes/functions?

2. The *target* of ML is a representation

3. Getting business *value* from ML requires reasoning for analysis and decisions

Why Combine KRR with ML (II)

4. KRR is required to *combine* results of ML from
   a. Multiple episodes
   b. Multiple sources
   c. Multiple methods

5. KRR is required to *accumulate* knowledge coherently
   - Weakness of ML today
   - Think cultural transmission

Why Combine KRR with ML (III)

6. KRR is required to *explain* knowledge understandably to humans
   - Weakness of ML today
   - Needed for humans to trust an automated system
   - Often part of required/desired analysis functionality for own sake

Why Combine KRR with ML (IV)

7. Reasoning to *supply derived facts* for ML to chew on as training examples or background info
   - This could be pulled by an ML system via backchaining

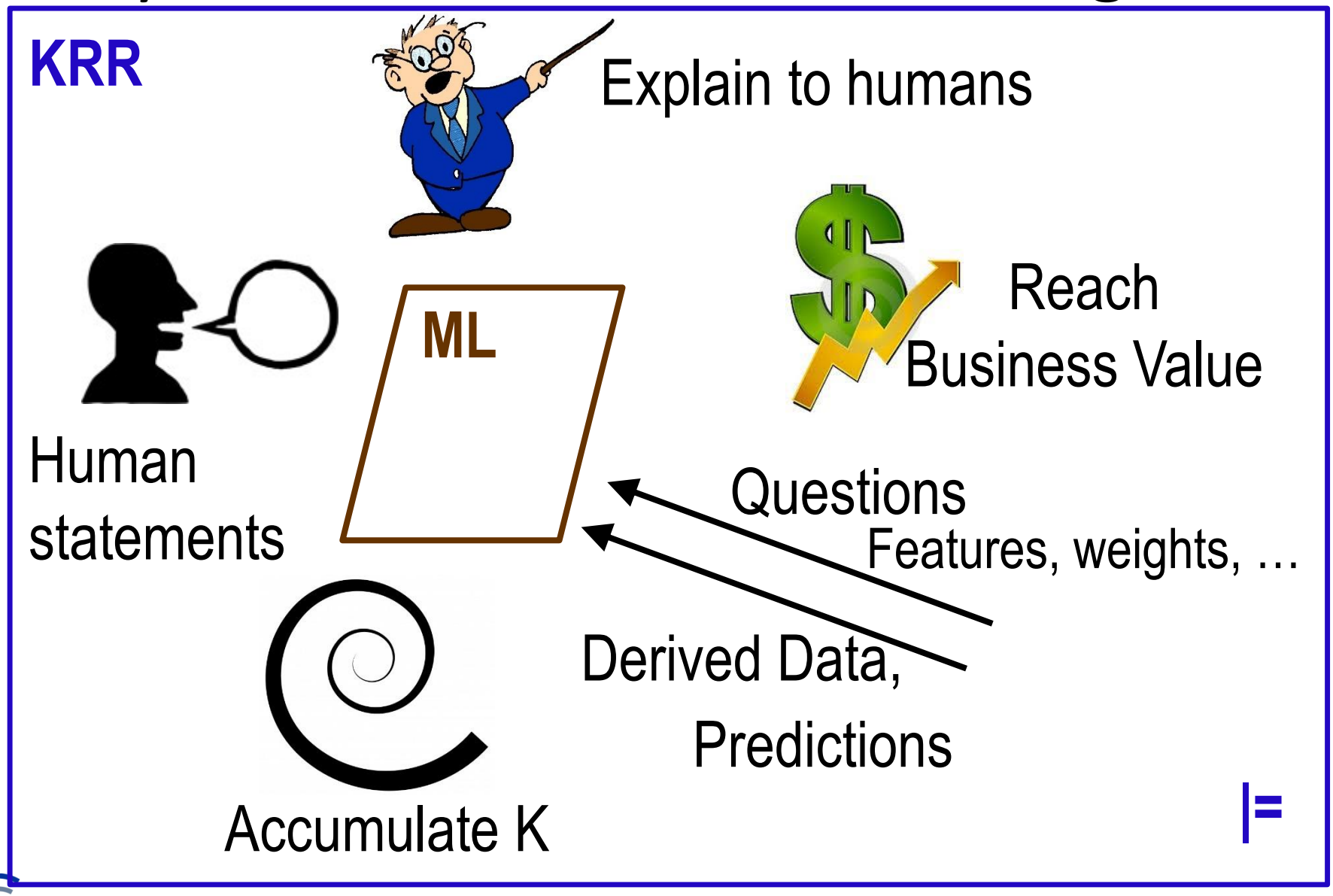
8. *Humans know stuff* beyond what's available via ML training data, and such knowledge is often complex to state / enter
   - KRR methods for entry/often more cost-effective than programming

Why Combine KRR with ML (V)

9. Reasoning is desirable to *pose questions* (tasks) to ML
   - as reasoning (sub)goals from KRR

10. Reasoning is desirable to *provide sets of relevant features, parameters, and/or weights* to ML

Why Combine KRR with ML – Diagram



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KRR Expressive Requirements for combination with neuro/ML (I)

Highly flexible expressiveness:

- Higher-order syntax
- Quantified formulas
- Strong meta (statements about statements)
- Numeric uncertainty (including weighting)
  - (thus differentiability)
  - Including probabilistic and fuzzy
- Defeasibility (exceptions)
  - Treat the evolving character of knowledge and of the world

KRR Scalability Requirements for combination with neuro/ML (II)

- Scalable computationally
  - To large amounts of asserted and concluded knowledge, i.e., “volume” and “velocity”

- Scalable “socially” to multiplicity of diverse knowledge, i.e., “variety”
  - To multiplicity of diverse ML/etc. sources, e.g., org.’s
  - To multiplicity of diverse ML/etc. algorithmic methods
  - To multiplicity of diverse underlying ML data samples

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Coherent Knowledge: Company Overview

- Fundamentally new kind of logic/rule based AI software platform for advanced analytics: flexible deep reasoning + natural language processing
- Radical business benefits: accuracy/competence, cost, agility, transparency
- Company offers: software product Ergo + professional services for custom solution dev
  - Capabilities: engine + development environment, for executable knowledge bases (logic/rules) embedded in apps
- World-class founder team: created many industry-leading logic systems & standards
  - Extensive experience applying logic systems to financial, regulation/policy, and other domains
  - Former/current professors at Stony Brook University and MIT

Michael Kifer, PhD
Principal Engineer
Prof., Stonybrook Univ.
Winner, 3 ACM & ALP test-of-time research awards.

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Data Science at Yale, US Forest Service.

Coherent Knowledge

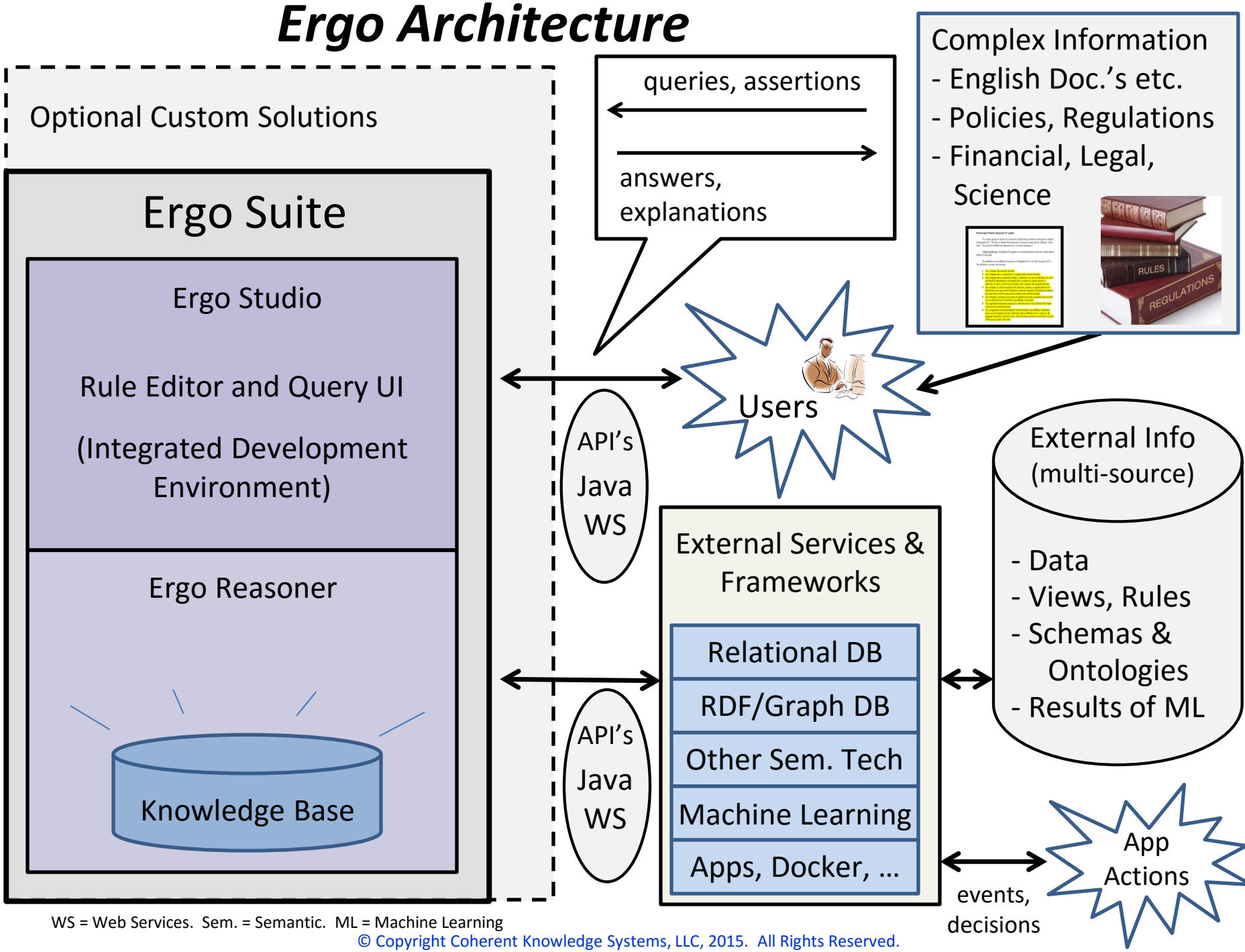
Rulelog and Textual Rulelog

- *Rulelog* is a kind of logical knowledge representation and reasoning (KRR)
  - A major research advance in KRR theory & algorithms, which culminated in 2012
- **Ergo is the most complete & highly optimized implementation available**
- Rulelog features very high/flexible expressiveness:
  - **Higher-order, general quantified formulas** (with logical chaining);
  - **Defeasibility (i.e., exceptions and argumentation)**;
  - Provenance, probabilistic, restraint bounded rationality, and more
- Yet Rulelog reasoning scales well: polynomial-time, as in databases
  - Millions of sentences concluded/asserted on a single processor
  - Up to trillions by orchestrating database etc. systems in distributed settings
- *Textual* Rulelog extends Rulelog with natural language processing (NLP)
  - Logic itself is utilized to map between English syntax and logic syntax
  - ErgoText templates aid knowledge entry and explanation generation

Series of Advances → Rulelog's Core Expressive Features

- Well-founded semantics; basic tabling algorithms
  - *Undefined* for paradox; smart cacheing; intuitionistic disjunction
- Higher-order syntax (Hilog); frame syntax
  - Associated optimizations of LP tabling etc. algorithms
- Statement id's for meta; argumentation meta-rules for defeasibility; provenance
- General formulas with all usual classical connectives and quantifiers (omniformity)
- Restraint bounded rationality
  - Use 3rd truth value *undefined* for "don't-care"
  - Radial, skipping; naf unsafety; external-query unsafety, unreturn

Ergo Architecture



WS = Web Services. Sem. = Semantic. ML = Machine Learning

Ergo Makes Sentences Executable

- If *something* is true then *something else* must be true. Written as:

then if

something_else :- *something*

- Example of <u>executable</u> Ergo sentence:

\(The individual affiliate threshold for transaction under Regulation W by ?Bank with ?Counterparty is ?Amount\) :-

\(?Counterparty is deemed an affiliate of ?Bank under Regulation W\) \and
\(?Bank has capital stock and surplus ?Capital\) \and
\(the threshold percentage for an individual affiliate is ?Percentage\) \and
?Amount = ?Capital * ?Percentage/100.

ErgoText

- ErgoText:

\(The proposed transaction ?Id by ?Bank with ?Affiliate of $?Amount is a RegW covered transaction\)

- ErgoText Template:

```
template(headbody,
        \(The proposed transaction ?Id by ?Bank with ?Affiliate of $?Amount
          is a RegW covered transaction\),

        covered(proposed(transaction))(by(?Bank))(with(?Affiliate))
          (of(amount(?Amount)))(having(id(?Id)))
        ).
```

- The templates are self-documenting

Textual Rulelog (III)

- Almost any NL sentence can be represented as a logical sentence
  - Leverages the <u>logical quantifiers</u> feature of Rulelog
  - Ex.: "each large company has some talented CEO"
    - forall(?x)^((?x \isa \(large company\)) ==>
      exists(?y)^((\?x has ?y\) \and
      (?y \isa \(talented CEO\)))).

Why is the proposed transaction prohibited by Regulation W?

3. *(continued) Why is the aggregate-affiliates limit $10 million?*

Why 'What proposed transactions are prohibited by RegW? Show '('Pacific Bank','Maui Sunset',23.0) ?

Edit Operations

- RegW prohibits the proposed transaction by Pacific Bank with Maui Sunset of $23.0 million
  - The proposed transaction by Pacific Bank with Maui Sunset of $23.0 million is a RegW covered transaction
  - There is a limit of $10.0 million for any proposed RegW covered transaction by Pacific Bank with Maui Sunset
    - There is an aggregated-affiliates limit of $10.0 million for any proposed RegW covered transaction by Pacific Bank with any affiliate
      - The aggregated total of previous RegW covered transactions by Pacific Bank with all affiliates is $490.0 million
      - The maximum threshold for aggregate RegW covered transactions by Pacific Bank with all affiliates is $500.0 million
        - The capital stock and surplus of Pacific Bank is $2500.0 million
        - The RegW threshold percentage for aggregate affiliates is 20.0 percent
        - $500.0 million is $2500.0 million multiplied by 20.0 percent
      - The limit of $10.0 million is the result of subtracting the previous RegW covered transactions total of $490.0 million from the RegW threshold $500.0 million
    - There is an individual-affiliate limit of $250.0 million for any proposed RegW covered transaction by Pacific Bank with Maui Sunset
    - The overall RegW limit of $10.0 million is the lesser of $10.0 million and $250.0 million
  - The proposed transaction of $23.0 million is greater than the RegW limit of $10.0 million

Business Benefits of Textual Rulelog for Analytics

- Deep in reasoning & knowledge
- Accurate
- Transparent, with explanations
- More Cost-Effective & Agile
- More Automated
- Easy to modify,
  end users empowered
- Greater Integration
- Greater Reusability
- What-if analyses

Analyze

Explain

Make Decisions

Monitor & Alert

Answer Questions

Application Areas for Rulelog (I)

- *Commercially, to date:*
- Financial regulatory/policy compliance
- Defense intelligence analysis
- Info integration: defense, financial, supply chain
- E-commerce pricing/promotion policies

Application Areas for Rulelog (II)

- *Explored in research, to date*
  … & promising commercially as further sub-areas

- Confidentiality policies: security, social media, HIPAA

- Financial/business reporting: XBRL

- Contracts: e-commerce, financial instruments, license agreements, large construction

- Health: treatment guidance, insurance

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Application Areas for Rulelog (III)

- *Explored in research, to date*
  … & promising commercially further areas

- Education/e-learning: personalized tutoring

- NL understanding and conversational interfaces

- Workflow / business process management: helpdesk, personal communications

KRs for Neuro-Symbolic: Candidates and Pros/Cons (I)

- Rulelog limitations:
  - Lacks "reasoning-by-cases", a.k.a. it is "intuitionistic"
    - Only concludes a disjunction if it concludes one of the disjuncts
  - Not yet optimized for numeric uncertainty reasoning
- Classical logic (first-order / higher-order):
  - Has reasoning-by-cases. But …
  - Lacks defeasibility
    - Brittle in face of conflicting/evolving K
    - Lacks social scalability
  - Lacks computational scalability, restraint
  - Lacks rule id's – hook for important kinds of meta

KRs for Neuro-Symbolic: Candidates and Pros/Cons (II)

- Markov Logic Networks
  - Attractively flexible and principled in numeric uncertainty
  - Has reasoning-by-cases
  - Much less computationally scalable than Rulelog
    - Though there are some tractable cases, they are restrictions
  - Lacks some key strong meta features, e.g., higher-order, id's
- Answer Set Programs (ASP)
  - Has reasoning-by-cases
  - Much less brittle than classical logic
  - Lacks computational scalability
  - Lacks some key strong meta features, e.g., rule id's

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Some Rulelog Lessons for Neuro-Symbolic

- Flexible expressiveness of rules
  - Doable practically. Very beneficial.
  - Specific constructs: HiLog, rule id's, defeasible, quantifiers, meta
  - Extend to NL via templates and parsing+quantification
    - Human-machine logic
  - Need to optimize probabilistic –ish weighted
- Explanation
  - Doable practically. Very beneficial.
  - Rule notion is very accessible to people.
  - Present justification digraph (with cycles) as tree with drill-down

Directions for Future Research

- Hook up Rulelog implementations to NN/ML systems
  - Potential applications include:
    - Compliance and fraud
    - NL understanding
      - Intelligence analysis
      - Search
- Analyze & compare more KRs tha are probabilistic/weighted + logic
  - e.g., in statistical relational
  - e.g., probabilistic soft logic

Future Research Directions: Core Technology and Experiments

- Feed derived data from Rulelog to NN (or ML)
  - Could be push or pull
- Combine NN results with other knowledge
  - E.g., with human-authored complex knowledge
    - Terminology mappings
    - Source trustworthiness
- Combine NN word-vector distributed representations with Textual Rulelog

Future Research Directions: on Rulelog KRR itself

- Optimize, and study further: Rulelog reasoning with uncertainty that is numerically weighted, including probabilistic and fuzzy

- Extend Rulelog's expressiveness to selective reasoning-by-bases

Thank you.

Deep Reasoning for Advanced Analytics

http://coherentknowledge.com