Cases, Networks and Knowledge: Learning to Leverage Experiences

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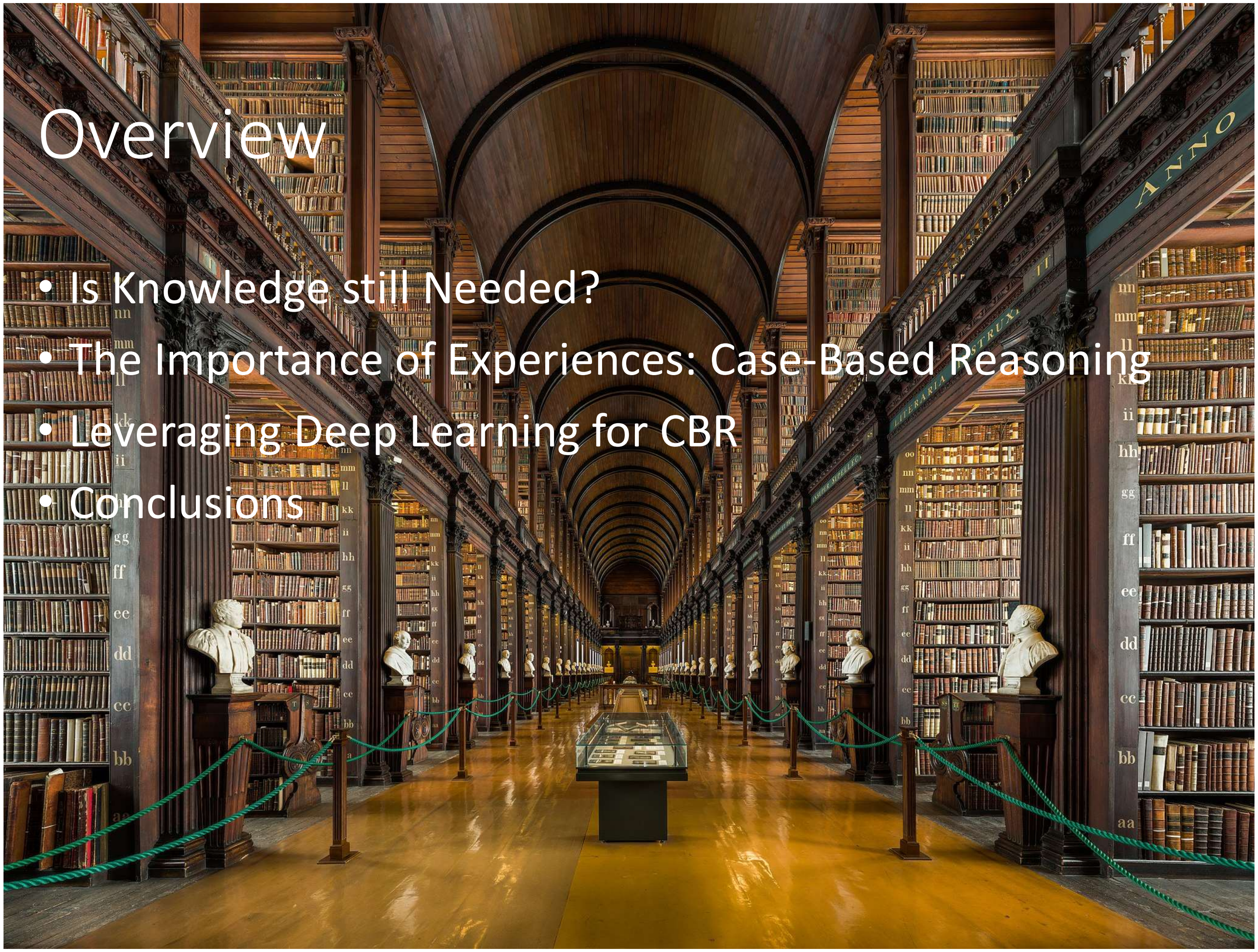
Overview

- Is Knowledge still Needed?
- The Importance of Experiences: Case-Based Reasoning
- Leveraging Deep Learning for CBR
- Conclusions



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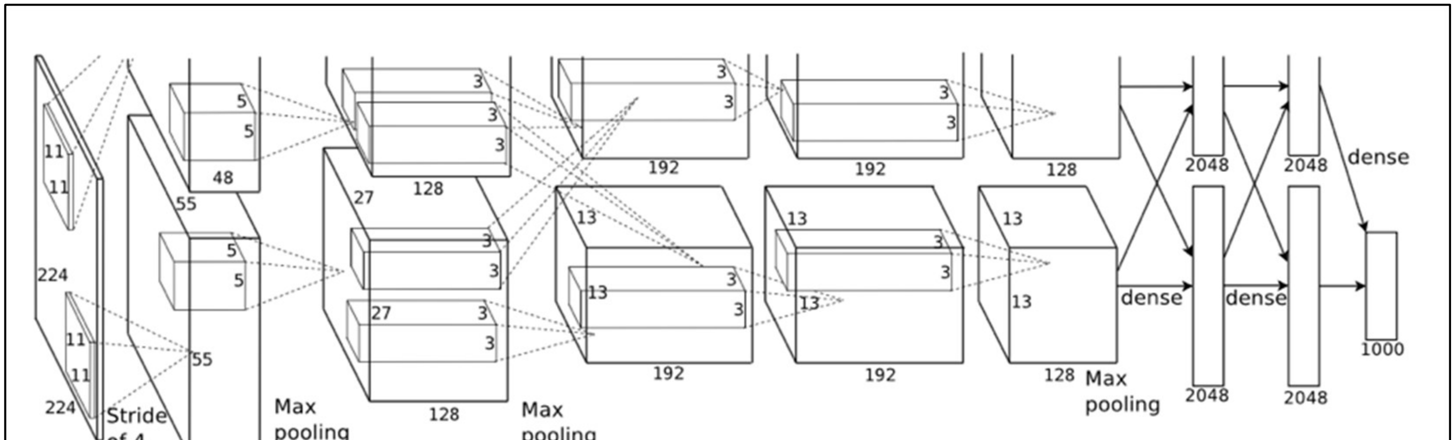
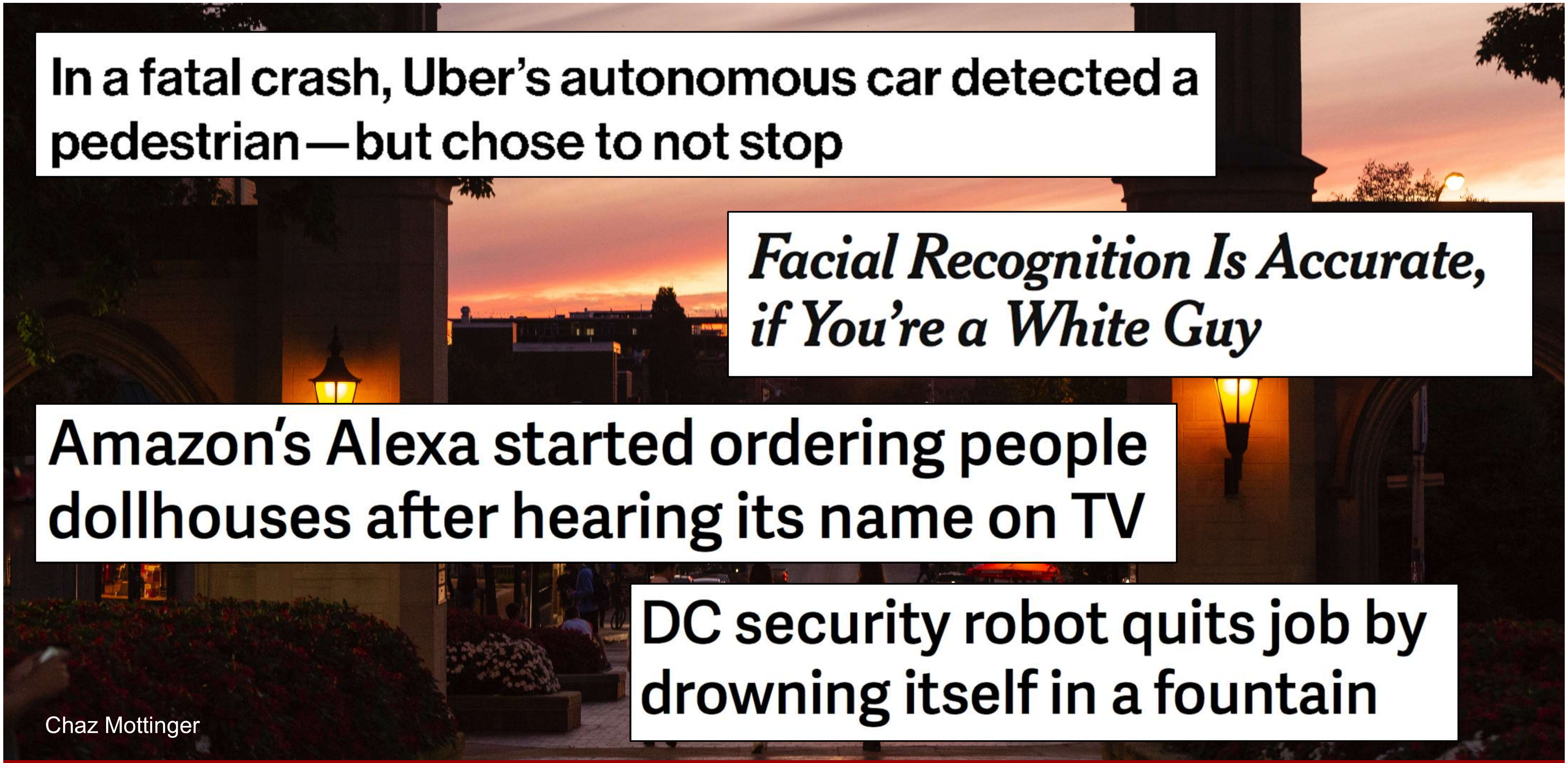
Facebook's Facial Recognition 'Approaching Human-Level Performance'
New computer program first to recognize sketches more accurately than a human
A Computer Can Recognize Emotions Better Than Most People
Artificial intelligence better than humans at spotting lung cancer

The Deep Learning Revolution

- Resurgence of neural networks in AI, powered by fast computers and massive datasets



Krizhevsky 2012



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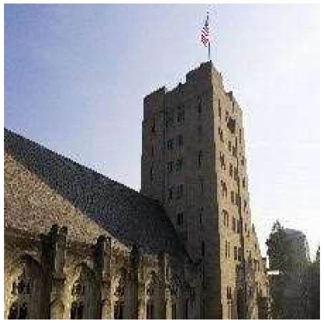
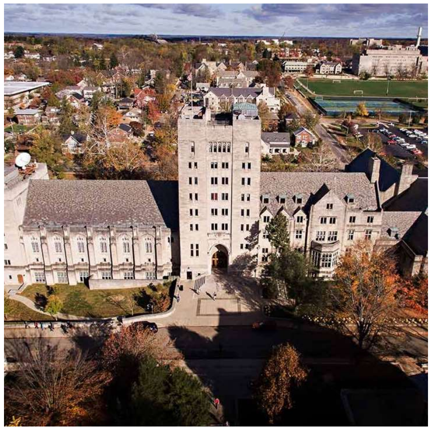
church

ladybug



chihuahua

Christmas stocking



Indiana Memorial Union

Zhenhua Chen

In Spite of its Successes, Deep Learning has Limitations (cf. Kursuncu, Gaur, Sheth, 2020)

1. Requires large training datasets/computing resources
2. May not generalize appropriately/can learn bias
3. Does not offer explainability
4. Cannot be easily trained on-line
5. Cannot easily incorporate human knowledge
6. Is susceptible to adversarial attacks

Knowledge Infused Learning (K-IL): Towards Deep Incorporation of Knowledge in Deep Learning Ugur Kursuncu , Manas Gaur , Amit Sheth, AAAI-MAKE 2020

``In the Knowledge Lies the Power"

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This Motivates Integrations—But How?

- Some options:

1. Incorporating external knowledge to support DL (e.g., for preprocessing/feature extraction)
2. Deep knowledge infusion, incorporating knowledge within hidden layers (Kursuncu , Gaur, & Sheth 2020)
3. Leveraging knowledge-based approaches with DL

Desiderata for the Integration

- Support acceptance: trust, traceability, and interactivity
- Facilitate knowledge capture
- Able to integrate information across multiple sources
- In particular, support integration of knowledge graphs/symbolic knowledge

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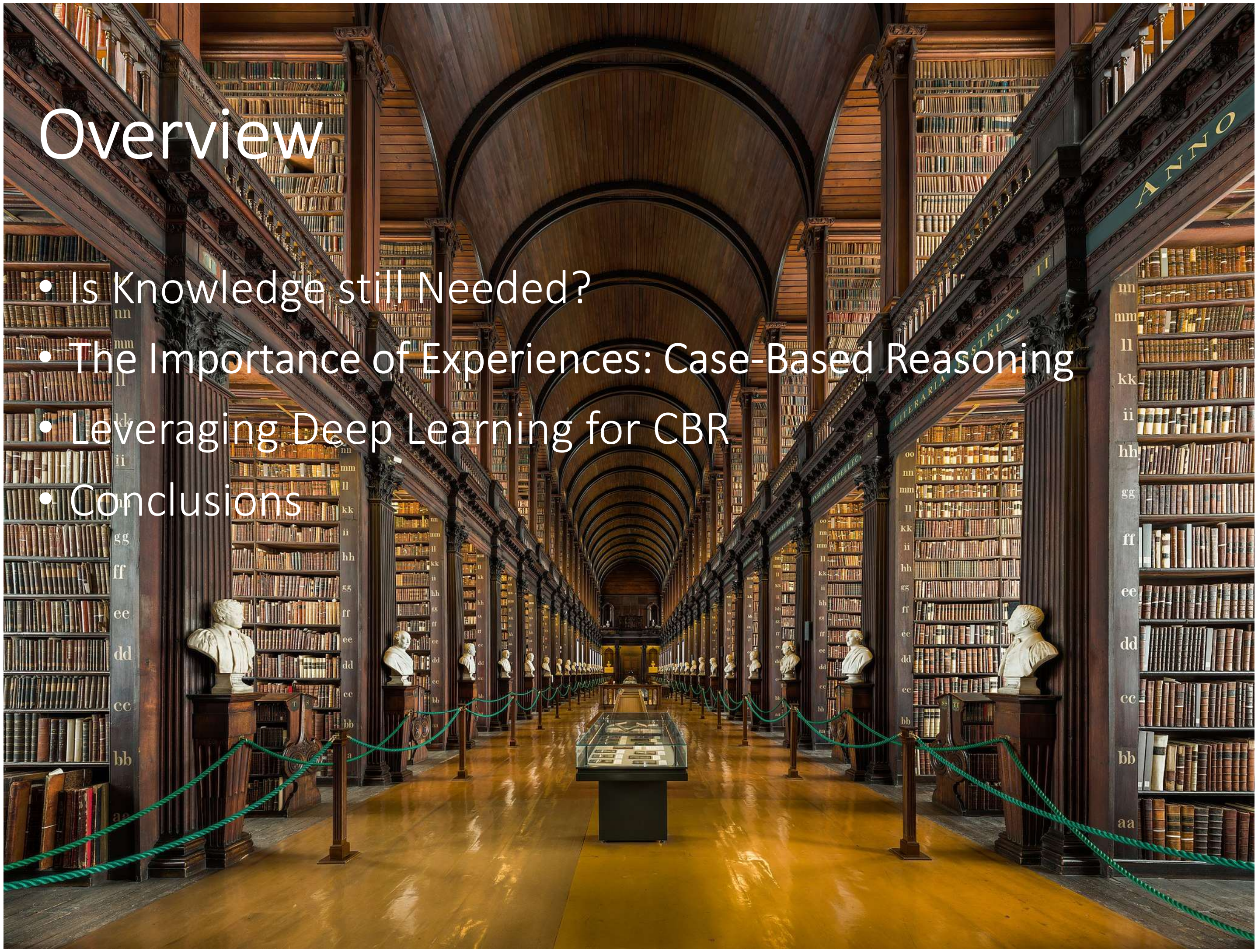


People Often Reason from Past Cases

In a [medical] conference … the chief of a service [asks] not for the latest news of research from the journals but for an anecdote: Anybody had any experience with this? (Hunter, 86)

A Replay of Vietnam in Iraq?
Boston Globe

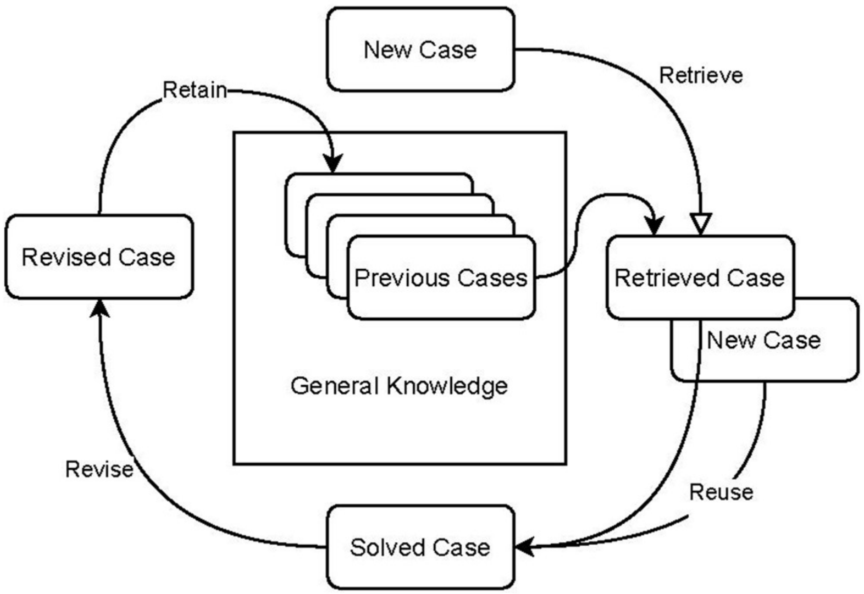
COVID-19 and 1918 'Spanish flu' have one depressing thing in common
Marketwatch

Studies support human reasoning from past cases for programming, explanation, diagnosis, decision-making…

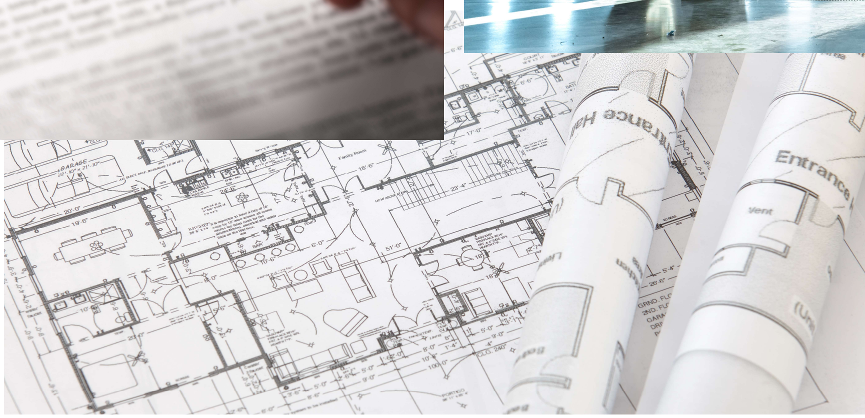
Case-Based Reasoning

CBR = Memory + Analogical mapping + Adaptation to fit

The Case-Based Reasoning Cycle



Knowledge-Rich Cases



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Practical Motivations for CBR Systems

- Reasoning/Learning from limited data, benefitting from prior knowledge
- Inertia-free learning
- Knowledge engineering benefits
  - Experts share “war stories” -> Cases may be easier to capture than rules
  - Knowledge can be acquired wherever convenient: vocabulary, cases, similarity, adaptation
- Explainability

Basis for Case-Based Reasoning System Quality
(Kolodner & Leake, 1996)

- The experiences it has had or been given,
- Its ability to understand the relevance of old experiences to new situations,
- Its adeptness at adapting prior solutions to fit new situations
- Its adeptness at evaluation of new solutions and repair flawed solutions, and
- Its ability to integrate new experiences into its memory appropriately

The CBR Knowledge Containers

- Vocabulary
- Case base
- Similarity knowledge
- Case adaptation knowledge

Key Challenge: Knowledge for Applying Cases

- Identifying case features
- Generating similarity criteria
- Generating case adaptation rules

Our Goal: Address with machine learning

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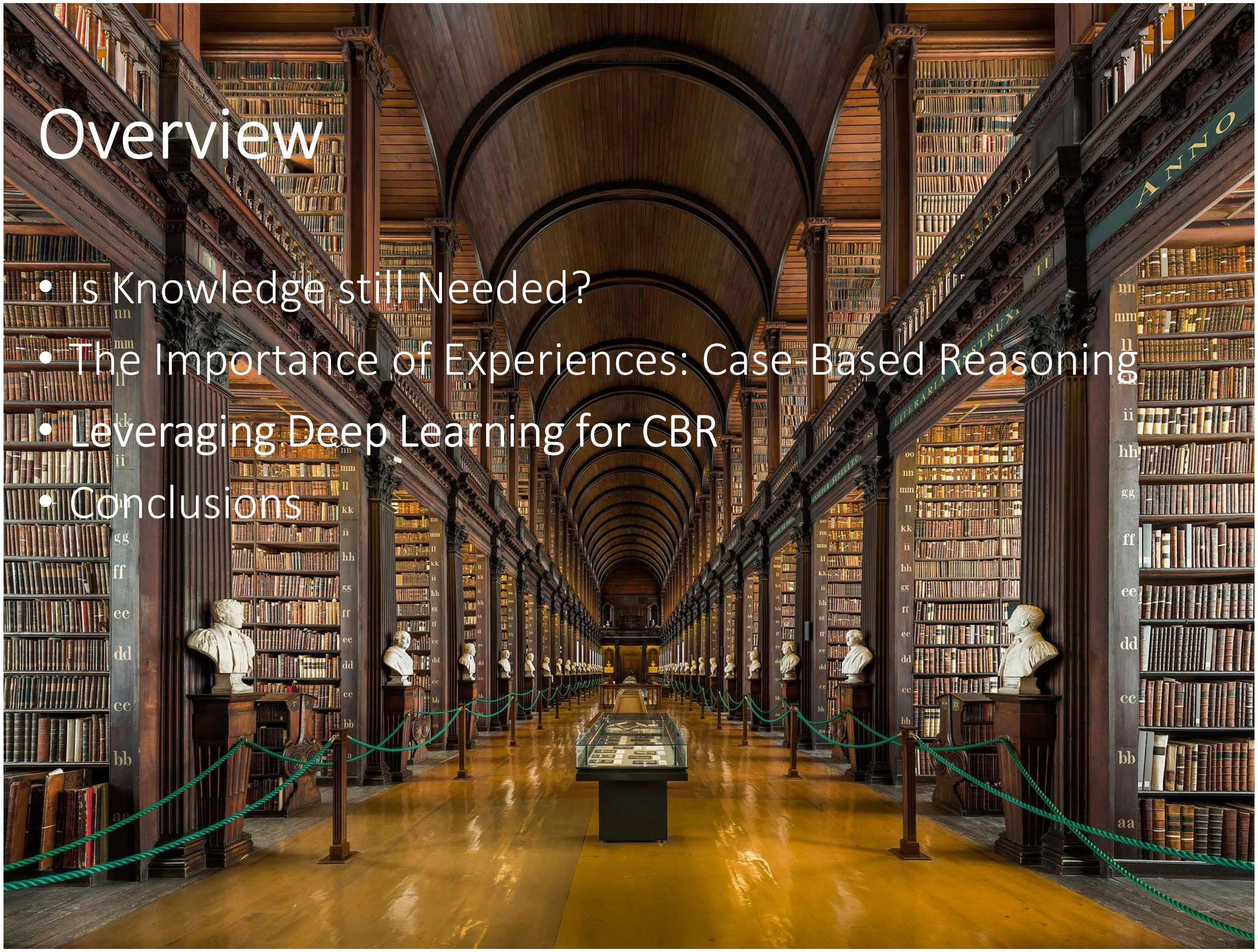


Goal: Synergistic Integration of DL and CBR

- Combine them to reinforce strengths/alleviate weaknesses of each
- Two avenues: Components and Pairings
- We've begun work on two components:
  - DL to improve CBR similarity assessment
  - DL to improve case adaptation

DL for Learning Case Similarity

- Siamese networks can learn similarity
- Learned similarity can improve case retrieval
- For classification, learning class-to-class patterns enables explanation of classifications not only by similarity but by relevant differences
- Additional ongoing work: Combining engineered and learned features

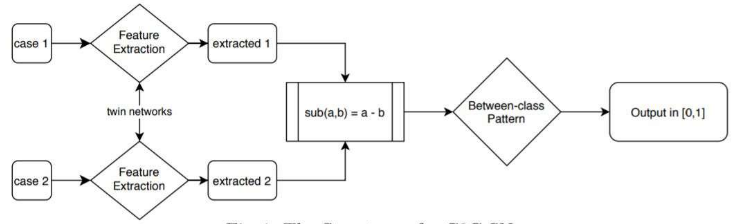


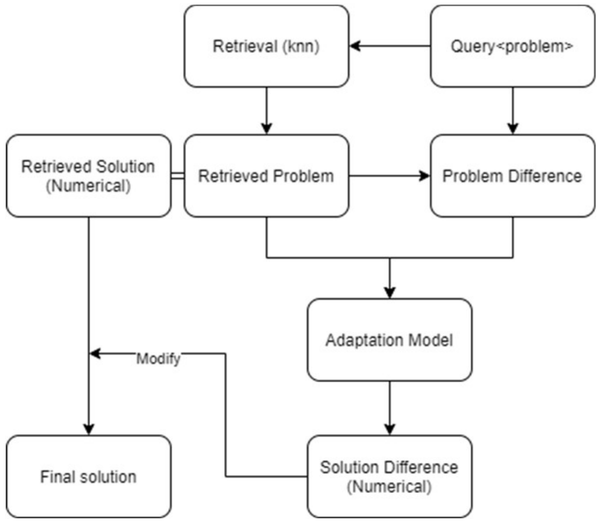
Fig. 1: The Structure of a C2C-SN

DL for Case Adaptation

- The "Case difference heuristic" approach (Hanney & Keane, 1997), generates adaptation rules from pairs of prior cases
- Their solution differences are ascribed to problem differences, yielding an adaptation rule
- E.g., comparing two apartments of different sizes and prices can yield a rule for how size changes affect price
- Obvious problem: How to generalize
- Appealing approach: Learn with a network (Liao, Liu and Chao 2018)

Network-Based Adaptation

- Collect pairs of cases (both neighboring pairs and random pairs).
- Train network to predict solution difference from
  - adaptation context (retrieved problem), and
  - problem difference (query - retrieved problem)
- Predict solutions by adjusting prior cases by learned solution differences



Evaluation

- Compares five systems:

1. K-NN with k= 1: Retrieval only; No adaptation.
2. K-NN with k= 3: Adaptation by averaging solutions.
3. CBR + normal CDH: Adaptation by applying solution difference derived from the most similar prior pair
4. CBR + network CDH: Adaptation by a neural network which learns CDH adjustments reflecting adaptation contexts.
5. A neural network regressor.

Testing scenario adjusted to vary problem novelty

Effect of CBR + NN Adaptation

Error on Kaggle Car Domain

	Number of cases removed (ncr)					
	0	1	2	10	50	100
3-NN	0.106	0.216	0.560	1.623	1.477	1.768
1-NN	0.065	0.040	0.497	1.677	1.527	2.039
CBR + network CDH	**0.029**	**0.030**	**0.049**	**0.257**	**0.237**	**0.256**
NN	0.035	0.080	0.108	0.413	0.544	0.560
CBR + normal CDH	0.076	0.067	0.489	1.672	1.487	1.973

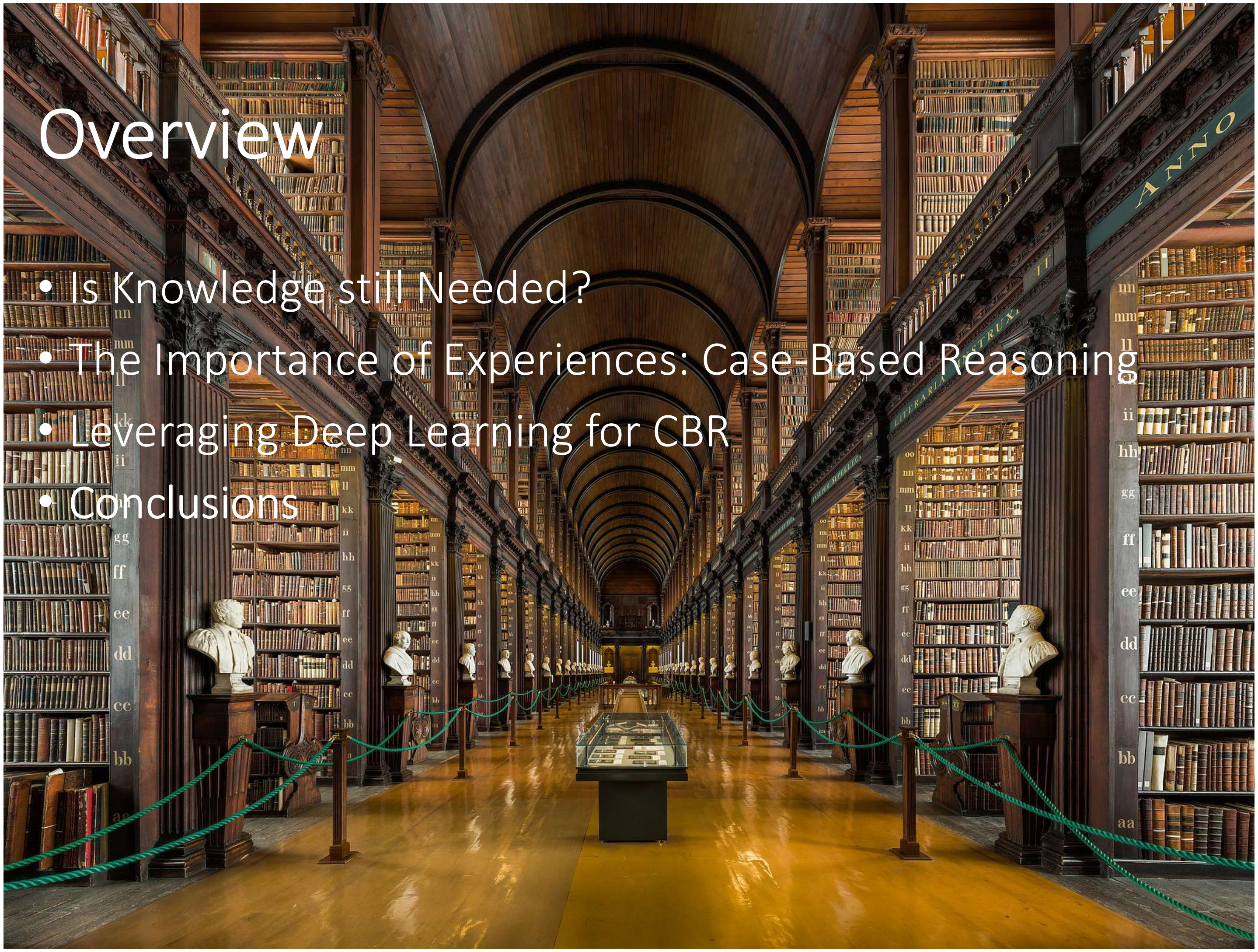
Leake, Ye, and Crandall, 2021

Summary of Results

- In low-dimensional test data set (airfoil), network CDH adaptation substantially improved over regular CDH adaptation
- However, the network alone outperformed CBR. Here, which to apply depends on tradeoff of explainability vs. performance
- In high-dimensional test set (car), network CDH substantially outperformed the other methods
- Benefit increased with query novelty
- Promising first step; now testing DL for features for CDH

Twin Systems

- Twin systems pair CBR and network systems (Keane & Kenny, 2019)
  - Both are trained on the same data and applied simultaneously
  - Results can be compared or case presented as explanation for the NN result
- NN supports data-driven flexibility
- CBR enables integration of knowledge and explainability
- Initial work: Estimating confidence (Gates, Kisby & Leake 2019)



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- Deep learning is a powerful tool for many problems, but also has inherent weaknesses.
- A possible path is combing Deep Learning with techniques that can explicitly reason from rich knowledge, like CBR, with complementary strengths and weaknesses.
- Key benefits: Ability to place knowledge in CBR and availability of cases for interpretability
- Upcoming at IJCAI: *Workshop on Deep Learning, AutoML, and CBR: Present and Future Synergies*

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Thank you!

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