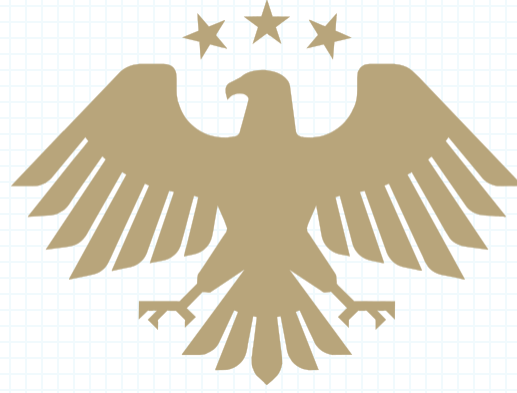




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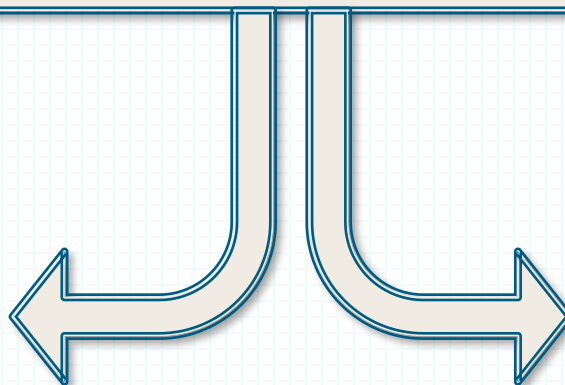
د. رياض سنبل

المعهد العالي للعلوم التطبيقية والتكنولوجيا

9/11/2025

استخدام الذكاء الصناعي في البحث العلمي

استخدام الذكاء الصناعي
للوصول **لحلول** للمسائل
البحثية المطروحة



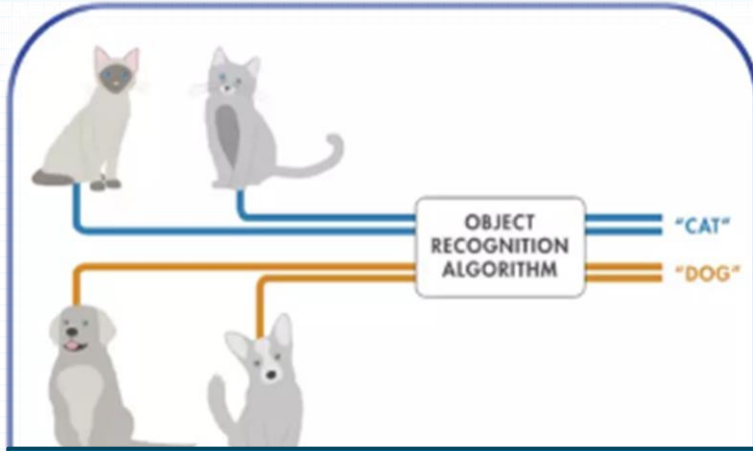
استخدام أدوات الذكاء
الصناعي كأدوات مساعدة
للمهام المختلفة

لمدة عاوة عن الذكاء الصناعي (لغير الهذتصين)

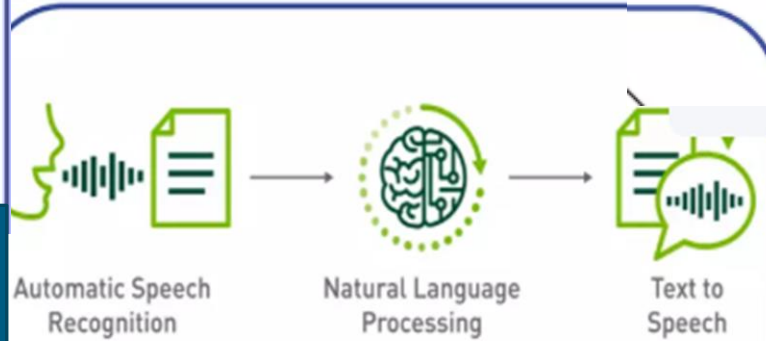
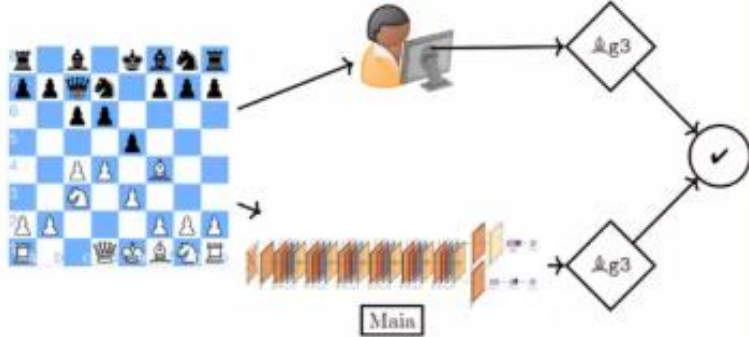
ما هو الذكاء الصناعي

- برمجيات حاسوبية قادرة على أداء أنشطة تشبه السلوك البشري، مثل
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 - الاستدلال واتخاذ القرارات،
 - وتصحيح الأخطاء ذاتياً وتطوير أدائها مع مرور الوقت.
 - ...

التعرف على الأغراض

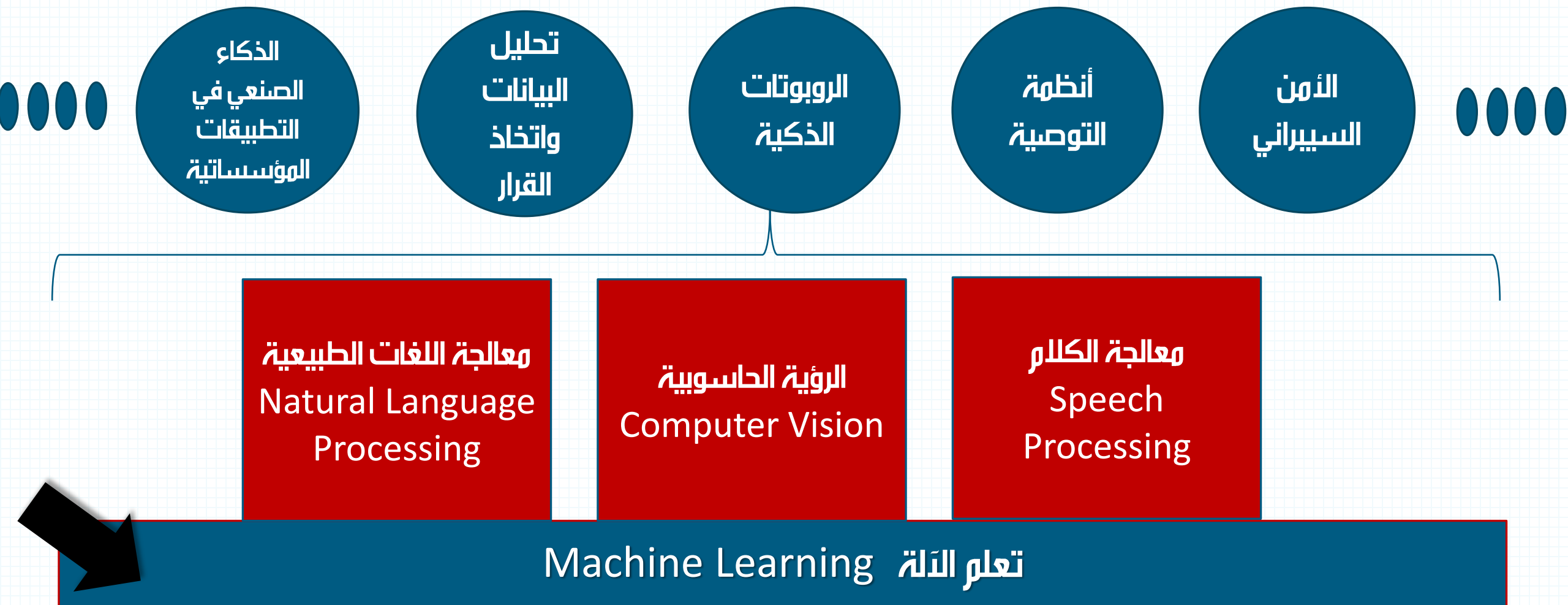


مهام تخطيط متقدمة ومعقدة

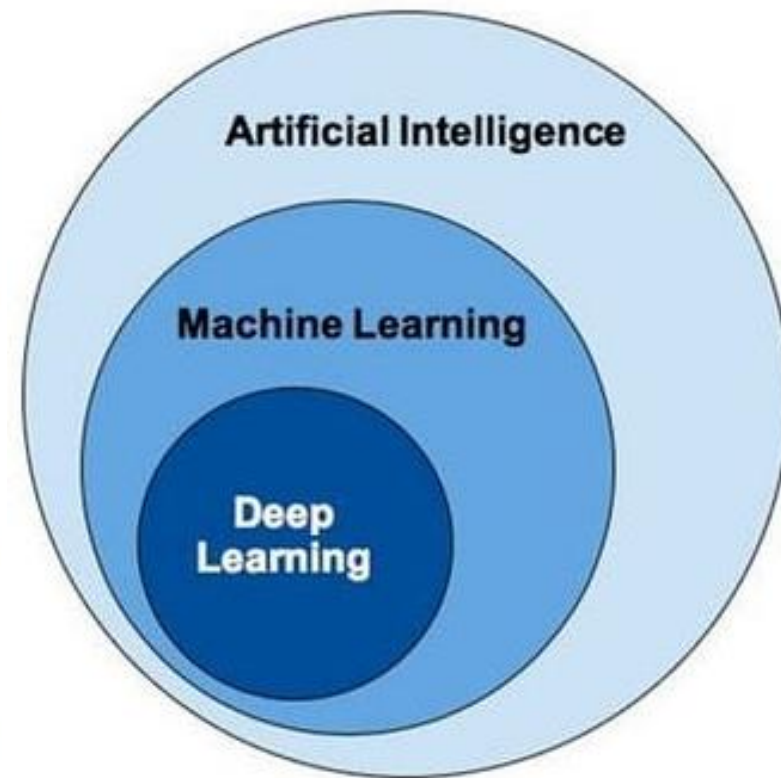
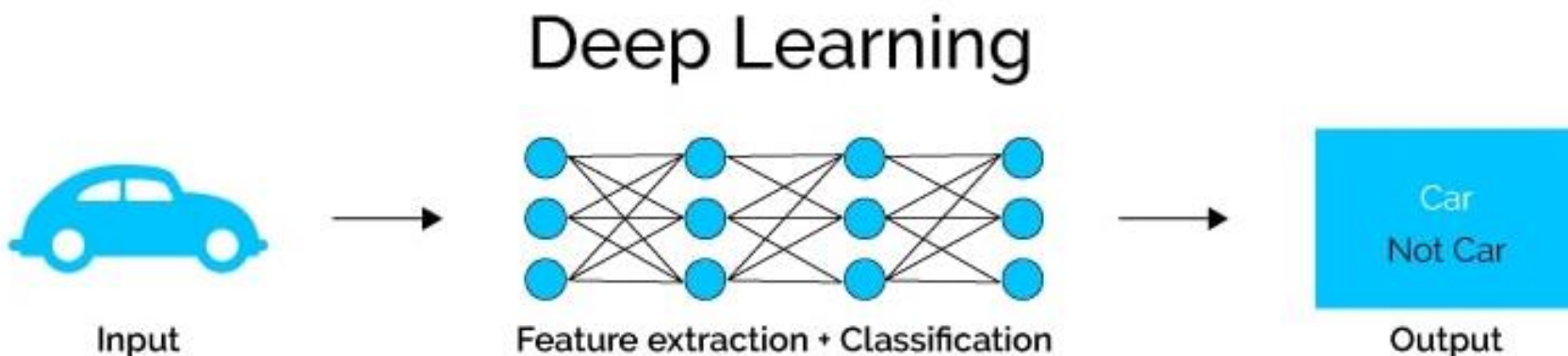
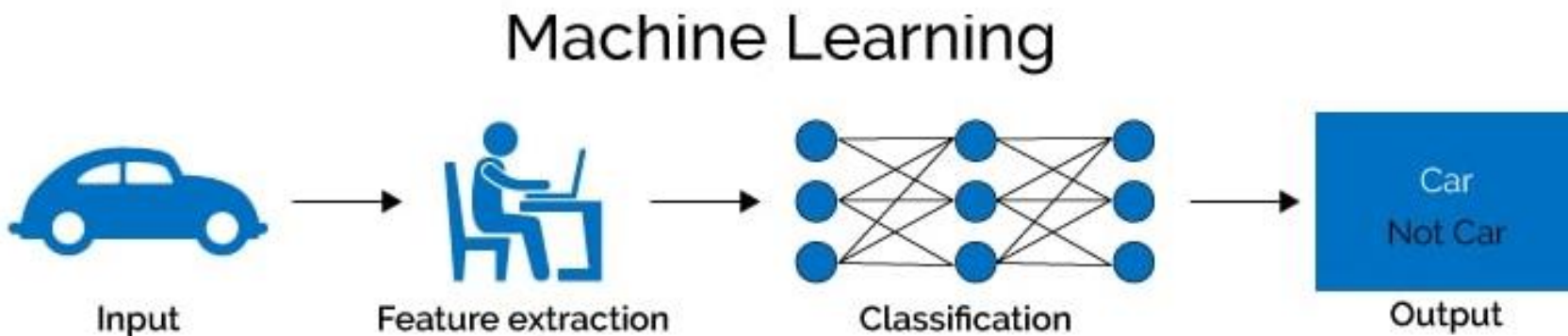


فهم اللغة، التعرف على الكلام،
الترجمة، إلخ

ما هو الذكاء الصناعي



تعلم الآلة vs التعلم العميق



كيف يمكن أن يساعد الذكاء الصناعي في البحث العلمي

الذكاء الصناعي ومهام البحث العلمي

■ يساعد الذكاء الصناعي على إنجاز المهام بشكل أسرع وأكثر فاعلية.

■ يمكن للباحث التركيز بشكل أكبر على الأعمال الأكثر أهمية (التحليل المعمق، التفكير النقدي، سؤال الأسئلة الصحيحة، ابتكار الحلول).

■ كباحث.. يجب أن تقود هذه الأدوات بحرفية.. لا أن تسلمها القيادة!



الذكاء الصناعي ومهام البحث العلمي



الذكاء الصناعي ومهام البحث العلمي

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المعرفة وصياغة
أسئلة بحثية دقيقة

تحديد مشكلة البحث وصياغتها

مراجعة الأدبيات

تصميم المنهجية أو الحل المقترح

جمع البيانات وتنفيذ الاختبارات

تفسير النتائج ومناقشتها

الكتابة والنشر العلمي

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ذات الصلة بسرعة
وتجميعها وتلخيصها
وتحليلها بكفاءة

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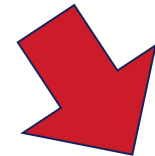
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Specificity

Performance outcome

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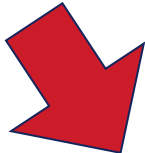
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What are the optimal printing temperature, extrusion rate, and layer height parameters for 3D printing medical-grade PEEK material using fused deposition modeling?



● Good research question. Consider adding these elements for better results:

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NOVEMBER 7, 2025

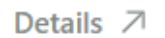
Which methods are most effective for generating semantic embeddings that capture sentence meaning in natural language processing tasks?

Encoder-only architectures combined with natural language inference data refinement and contrastive learning produce the most effective semantic sentence embeddings, with methods like Sentence-BERT and Sentence-T5 achieving superior performance on semantic textual similarity tasks.

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Which methods are most effective for generating semantic embeddings that capture sentence meaning in natural language processing tasks?

Encoder-only architectures combined with natural language inference data refinement and contrastive learning produce the most effective semantic sentence embeddings, with methods like Sentence-BERT and Sentence-T5 achieving superior performance on semantic textual similarity tasks.

Abstract

Sentence embeddings that capture meaning most effectively arise from encoder-only architectures refined by natural language inference (NLI) data and augmented with contrastive learning. Reimers and Gurevych (2019) present Sentence-BERT, which uses a siamese/triplet network with pooling to yield fixed-length vectors. Their method scores 11.7 points higher than InferSent and 5.5 points ahead of the Universal Sentence Encoder on semantic textual similarity (STS) benchmarks, while cutting inference time for 10,000 sentences from 65 hours (BERT) to 5 seconds on GPU and training in under 20 minutes.

Ni et al. (2021) detail Sentence-T5, which employs both encoder-only and encoder-decoder variants with a dual encoder and multi-stage contrastive approach. The encoder-only model exceeds previous baselines on SentEval and SentGLUE tasks and, when scaled from 220 million to 11 billion parameters, achieves throughput rates of 274 examples per second on a Cloud TPU-v3. Both approaches also show robust transfer learning performance across tasks such as sentiment analysis, paraphrase detection, and natural language inference.

Paper search

We performed a semantic search using the query "Which methods are most effective for generating semantic embeddings that capture sentence meaning in natural language processing tasks?" across over 138 million academic papers from the Elicit search engine, which includes all of Semantic Scholar and OpenAlex.

We retrieved the 50 papers most relevant to the query.

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Main Contribution

The main contribution of this paper is the proposal of **Supervised Reinforcement Learning (SRL)**, a novel training framework that addresses the limitations of existing methods for training small-scale language models on multi-step reasoning problems ¹.

Key Innovation

SRL reformulates problem solving as a sequence of logical "actions" and trains the model to generate an internal plan by committing to each action ². The



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● Ni, 2021

Sentence-T5: Scalable Sentence Encoders from Pre-trained Text-to-Text Models

Findings

We provide the first exploration of sentence embeddings from text-to-text transformers (T5) including the effects of scaling up sentence encoders to 11B parameters. Sentence embeddings are broadly useful for language processing tasks. While T5 achieves impressive performance on language tasks, it is unclear how to produce sentence embeddings from encoder-decoder models. We investigate three



Ni, 2021

● sentence embedding

Sentence-T5: Scalable Sentence Encoders from Pre-trained Text-to-Text Models

Findings

PDF

Jianmo Ni ... +5 Yinfei Yang

Add note...

We provide the first exploration of sentence embeddings from text-to-text transformers (T5) including the effects of scaling up sentence encoders to 11B parameters. Sentence embeddings are broadly useful for language processing tasks. While T5 achieves impressive performance on language tasks, it is unclear how to

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Devlin, 2019
Meaning similarity of sentences. Applications include machine translation (MT), summarization,

He, 2020

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Computer Vision and Pattern Recognition

We present Momentum Contrast (MoCo) for unsupervised visual representation learning. From a perspective on contrastive learning as dictionary

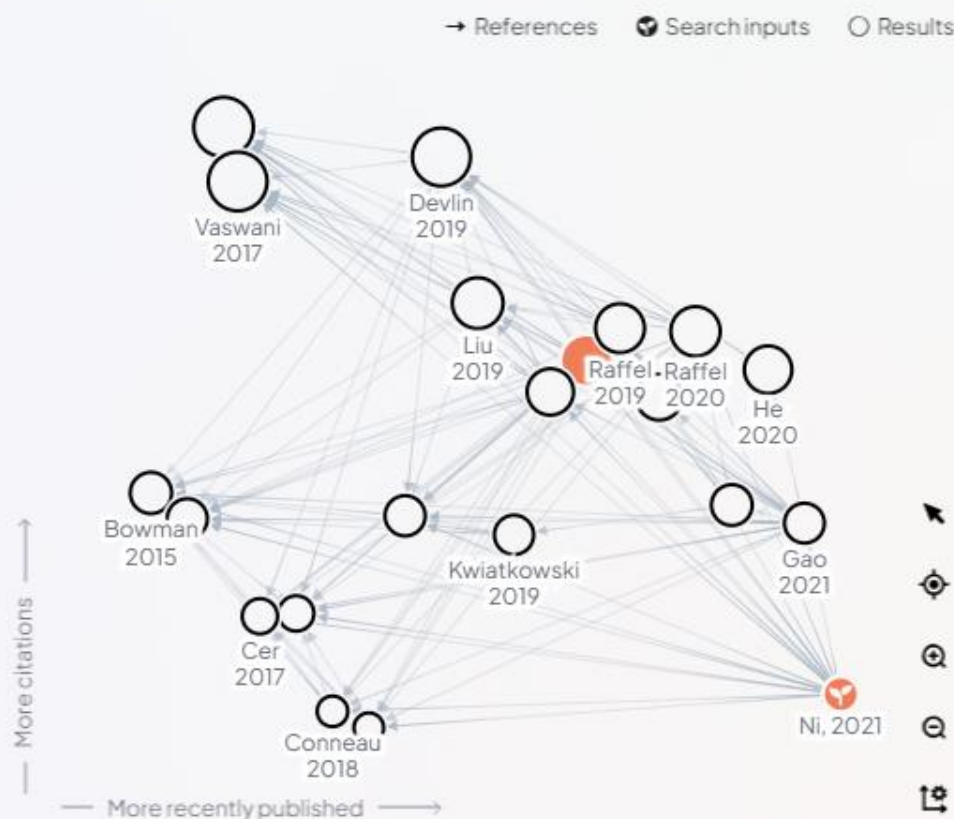
Williams, 2018

A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference

north american chapter of the association for computational linguistics

This paper introduces the Multi-Genre Natural Language Inference (MultiNLI) corpus, a dataset designed for use in the development and evaluation

< 1 - 20 of 1,460 >



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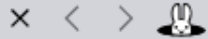
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Kingma, 2014

Adam: A Method for Stochastic Optimization

International Conference on Learning Representations

We introduce Adam, an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates

Lan, 2019

ALBERT: A Lite BERT for Self-supervised Learning of Language Representations

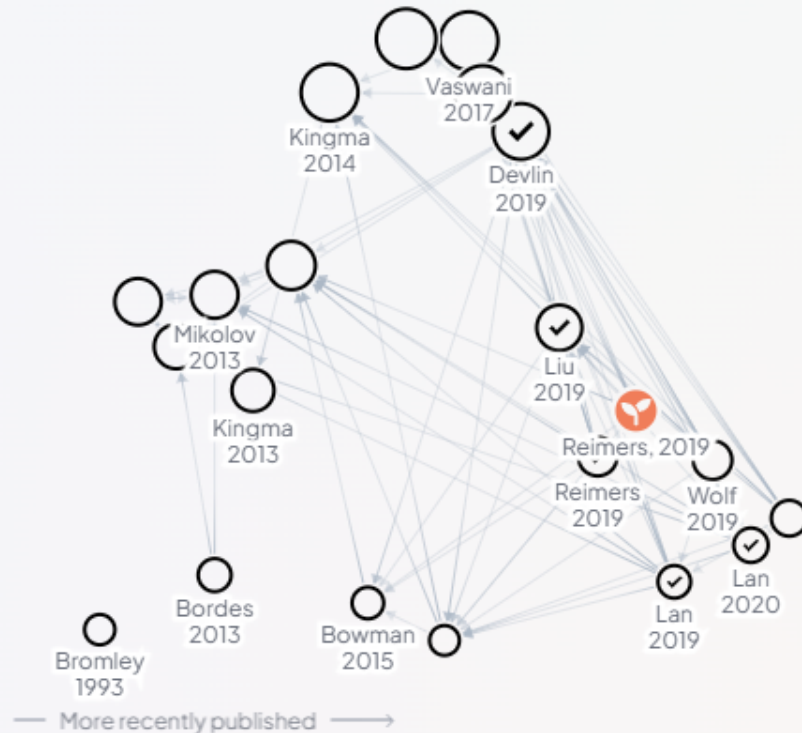
International Conference on Learning Representations

Increasing model size when pretraining natural language representations often results in improved performance on downstream tasks. However, at

Mikolov, 2013

Distributed Representations of Words and

More citations ↑



Bromley 1993

Bordes 2013

Bowman 2015

Kingma 2014

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Vaswani 2017

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Wolf 2019

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Devlin, 2019 BERT: Pre-training of Deep Bidirectional Transformers for Language

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	Lan, 2020	2020	ALBERT: A Lite BERT for Self-supervised Lea...	110	8,558	✓
	Liu, 2019	2019	RoBERTa: A Robustly Optimized BERT Pretra...	103	32,159	✓
	Devlin, 2019	2019	BERT: Pre-training of Deep Bidirectional Tra...	90	117,5...	✓
	Reimers, 2019	2019	Sentence-BERT: Sentence Embeddings usi...	56	15,5...	✓
	Ni, 2021	2021	Sentence-T5: Scalable Sentence Encoders ...	54	729	✓
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3 @article{albert_lan_2019,
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5   author = {Lan, Zhen and Chen, Mingda and Goodman, Sebastian and Gimpel, Kevin and Sharma, Piyush and Soricut, Radu},
6   journal = {International Conference on Learning Representations},
7   year = {2019},
8   researchRabbitId = {7fd55f38-2ef3-45a1-9b4d-6ec4e6ae6e11}
9 }
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11
12 @article{albert_lan_2020,
13   title = {ALBERT: A Lite BERT for Self-supervised Learning of Language Representations},
14   author = {Lan, Zhenzhong and Chen, Mingda and Goodman, Sebastian and Gimpel, Kevin and Sharma, Piyush and Soricut, Radu},
15   journal = {arXiv (Cornell University)},
16   year = {2020},
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22   title = {RoBERTa: A Robustly Optimized BERT Pretraining Approach},
23   author = {Liu, Yinhan and Ott, Myle and Goyal, Naman and Du, Jingfei and Joshi, Mandar and Chen, Danqi and Levy, Omer
24   and Lewis, Mike and Zettlemoyer, Luke and Stoyanov, Veselin},
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26   year = {2019},
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31   title = {BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding},
32   doi = {10.18653/V1/N19-1423},
33   author = {Devlin, Jacob and Chang, Ming-Wei and Lee, Kenton and Toutanova, Kristina},
34   journal = {North American Chapter of the Association for Computational Linguistics},
35   year = {2019},
36   researchRabbitId = {b66e85cf-145c-4bcf-8753-c6443a87a0f9}
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الذكاء الصناعي ومهام البحث العلمي



الذكاء الصناعي ومهام البحث العلمي





Goals

-- Overall score

BERT designed to pre train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers.



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- مثال: يستخدم طالب في علوم البيئة تقنيات التعلم الآلي للتنبؤ بالتغيرات في كثافة الغابات اعتمادًا على صور الأقمار الصناعية.
- **اكتشاف الأنماط والرؤى Uncovering Insights and Patterns**
- استخدام الذكاء الاصطناعي لاستخلاص العلاقات الخفية واتجاهات البيانات.
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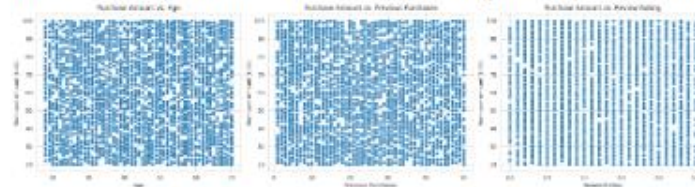
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plt.title(f'Average Purchase Amount by {col}')
plt.xlabel(col)
plt.ylabel('Average Purchase Amount (USD)')
plt.xticks(rotation=45, ha='right') # Rotati
```

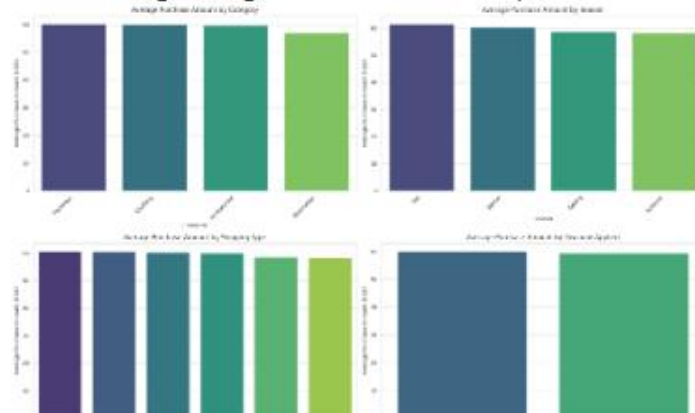
```
plt.tight_layout()
plt.show()
```

▼

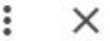
Visualizing Numerical Relationships with 'Purcha



Visualizing Categorical Relationships with 'Purcha



Gemini



R أجر تحليلًا تفصيليًا لهذه المعطيات يبين علاقة المبلغ المدفوع مقارنة ببيانات المعلومات

Shopping_behavior_updated.csv

♦ بالتأكيد، سأقوم بتحليل مفصل للبيانات لفهم العلاقة بين المبلغ المدفوع والمعلومات الأخرى. إليك خطة العمل:

- تحميل البيانات: تحميل ملف `/content/Shopping_behavior_updated.csv` في إطار بيانات بايثون.
- استكشاف البيانات: استكشاف بنية البيانات، مثل رؤوس الأعمدة وأنواع البيانات والإحصائيات الوصفية، وتحديد الأعمدة ذات الصلة بالمبلغ

Analyze the top 5 locations with the highest average purchase amount

Visualize the relationship between 'Category' and 'Purchase Amount (USD)'

Suggest actionable insights based on the categorical analysis

What can I help you build?



Gemini can make mistakes so double-check it and use code with caution. [Learn more](#)

Runtime disconnected



12:50 PM Connecting to Python 3

Google CoLab with Gemini

Commands + Code + Text Run all

RAM Disk

SUBTASK:

في إطار بيانات بانداس "/content/Shopping_behavior_updated.csv" تحميل ملف

Reasoning: First, I'll import the pandas library to enable data manipulation, then load the CSV file '/content/Shopping_behavior_updated.csv' into a DataFrame named 'df', and finally display the first few rows to confirm successful loading.

[1] 0s

```
import pandas as pd

df = pd.read_csv('/content/Shopping_behavior_updated.csv')

print("Data loaded successfully. Here are the first 5 rows:")
df.head()
```

Data loaded successfully. Here are the first 5 rows:

	Customer ID	Age	Gender	Item Purchased	Category	Purchase Amount (USD)	Location	Size	Color	Season
0	1	55	Male	Blouse	Clothing	53	Kentucky	L	Gray	Win
1	2	19	Male	Sweater	Clothing	64	Maine	L	Maroon	Win
2	3	50	Male	Jeans	Clothing	73	Massachusetts	S	Maroon	Spr

Gemini

R هل يمكنك إجراء تحليل أعمق للوصول لخلاصات عميقة من هذه المعلومات؟

♦ بالتأكيد، يمكننا إجراء تحليل أعمق للحصول على رؤى أكثر تفصيلاً. إليك خطة عمل مقترحة تركز على استكشاف التوزيعات والتفاعلات بين المتغيرات:

- **تحديد الميزات القنوية الرئيسية للتحليل المتعمق:** مراجعة نتائج التحليل القنوي السابق لتحديد الميزات التي أظهرت اختلافات ملحوظة في متوسط 'مبلغ الشراء' (بالدولار الأمريكي). ستكون هذه الميزات هي محور تحليل التوزيع.
- **تصور توزيع مبلغ الشراء للميزات القنوية الرئيسية:** إنشاء رسوم بيانية (Violin plots) أو رسوم بيانية كمانية (Box plots) صندوقية لتصور توزيع 'مبلغ الشراء' (بالدولار الأمريكي) للميزات القنوية الرئيسية. سيظهر هذا ليس فقط المتوسط ولكن أيضًا الانتشار، الأرباع، والمخرجات المحتملة ضمن كل فئة، مما يوفر فهماً أعمق من مجرد المتوسطات.
- **تحليل تأثيرات التفاعل بين المتغيرات القنوية:** التحقق في تأثيرات التفاعل المحتملة بين المتغيرات القنوية الرئيسية. على سبيل المثال، تحليل

What can I help you build?

Gemini can make mistakes so double-check it and use code with caution. [Learn more](#)

Google CoLab with Gemini



Gemini Example.ipynb ☆ Saving...

File Edit View Insert Runtime Tools Help



Share

Commands + Code + Text Run all

✓ RAM Disk



[12]

✓ 4s



```
num_cols = 2
```

```
for i, col in enumerate(key_categorical_features):  
    plt.subplot(num_rows, num_cols, i + 1) # Create subplot  
    sns.boxplot(x=col, y='Purchase Amount (USD)', data=df, palette='viridis', hue=col, legend=False)  
    plt.title(f'Purchase Amount Distribution by {col}')  
    plt.xlabel(col)  
    plt.ylabel('Purchase Amount (USD)')  
    plt.xticks(rotation=45, ha='right') # Rotate x-axis labels for readability
```

```
plt.tight_layout() # Adjust layout to prevent overlapping  
plt.show()
```



Variables

Terminal



✓ 1:10 PM

Python 3

الذكاء الصناعي... المسؤولية الأكاديمية

المسؤولية تقع على الباحث

◦ يجب على الباحث التحقق من كل معلومة أو ادعاء أو مرجع قبل اعتمادها.

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COUNTRY

United States

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SUBJECT AREA AND CATEGORY

Computer Science
└ Computer Science (miscellaneous)

Engineering
└ Engineering (miscellaneous)

Materials Science
└ Materials Science (miscellaneous)

H-INDEX

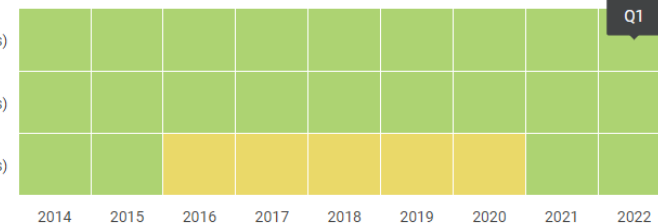
204

Quartiles

Computer Science (miscellaneous)

Engineering (miscellaneous)

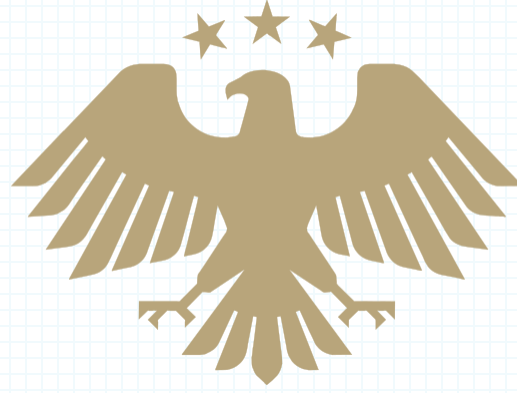
Materials Science (miscellaneous)



المسؤولية تقع على الباحث

- لا تضع أبدًا بيانات حساسة أو سرّية أو غير منشورة في أدوات الذكاء الاصطناعي العامة (مثل النسخ المجانية من ChatGPT)
- فقد تُستخدم البيانات المُحمّلة لأغراض تدريب النماذج.

AI handles the "how" (data processing, analysis), but you provide the "why" (the research question, the interpretation).



استخدام الذكاء الصناعي في البحث العلمي

د. رياض سنبل

المعهد العالي للعلوم التطبيقية والتكنولوجيا

