

Conversational AI: Unveiling the Magic Behind Pre-trained Large Language Models in Digital Assistants

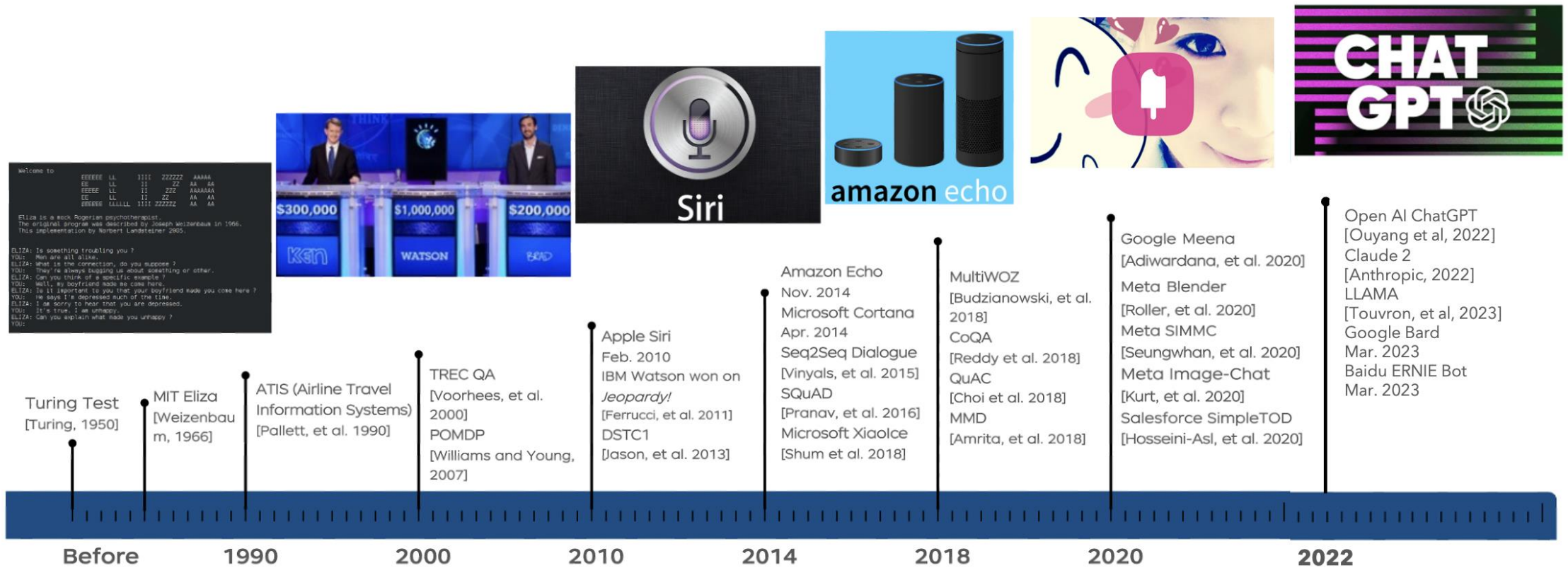
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<https://chenmengdx.github.io>

2023/11/30

History of Conversational AI

- Conversational AI is a subfield of artificial intelligence that focuses on enabling machines to engage in human-like conversation. It uses technologies like machine learning, natural language processing, and speech recognition to understand and respond to human language in a natural and intuitive way



Challenges of Conversational AI

- **NLU (Natural Language Understanding)**

Ambiguities, Handling variability, Context management, Slangs, typos, and abbreviations, domain knowledge

- **Understanding User**

User profile, personality

- **Difficulty in Communicating**

Multi-lingual, spoken language

- **Costly Investment**

High-quality real-scenario training data, computing resources

- **Public Skepticism**

public suspicion, misconceptions

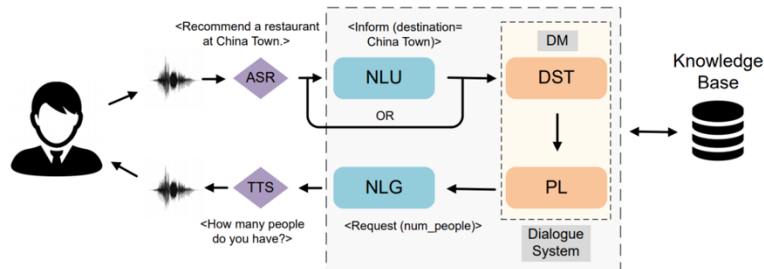
- **Unexpected Questions**

unanticipated customer interactions

Category of Dialogue System

Task-oriented Dialogue System

- Designed to help users achieve pre-defined tasks, such as booking tickets, ordering food, or scheduling calls
- Communicate with humans via text, speech, gestures, graphics, and other means.
- Often use a pipeline approach that employs a variety of modules, breaking the task into smaller sub-tasks.



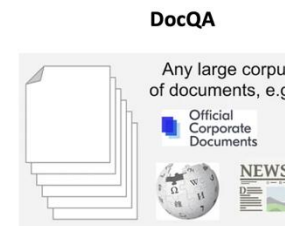
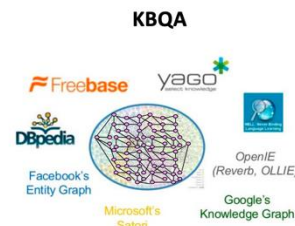
Question & Answering

- usually answer info-seeking questions posed by humans in natural language
- use different sources of information, such as qa pairs, tables/graphs, documents, or the web, to find the relevant answers



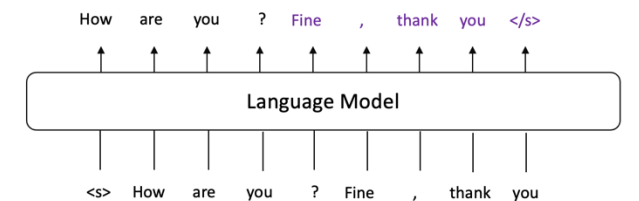
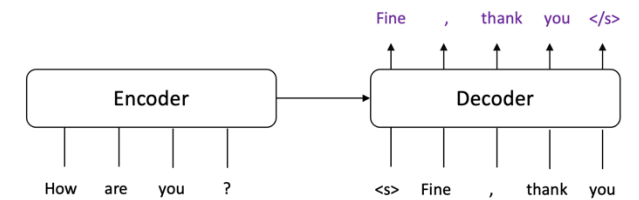
Table QA

Series	Title	Written By	Viewers (Million)
...
4	Pilot	Mikael Salomon	3.82
5	Healing Time	Arvin Brown	3.80
6	Night Moves	Roxann Dawson	3.61
7	Mother's Day	Jeff Bleckner	3.35
...



Open Domain Chit-chat

- a type of conversation that does not have a specific goal or topic, but rather aims to make the dialogue engaging, interesting, and natural
- chatbots that can generate responses to any user input, without being restricted by a predefined domain or task



Pre-trained Large Language Models

Large language models (LLMs): use transformer models and are trained using massive datasets, which enables them to recognize, translate, predict, or generate text or other content

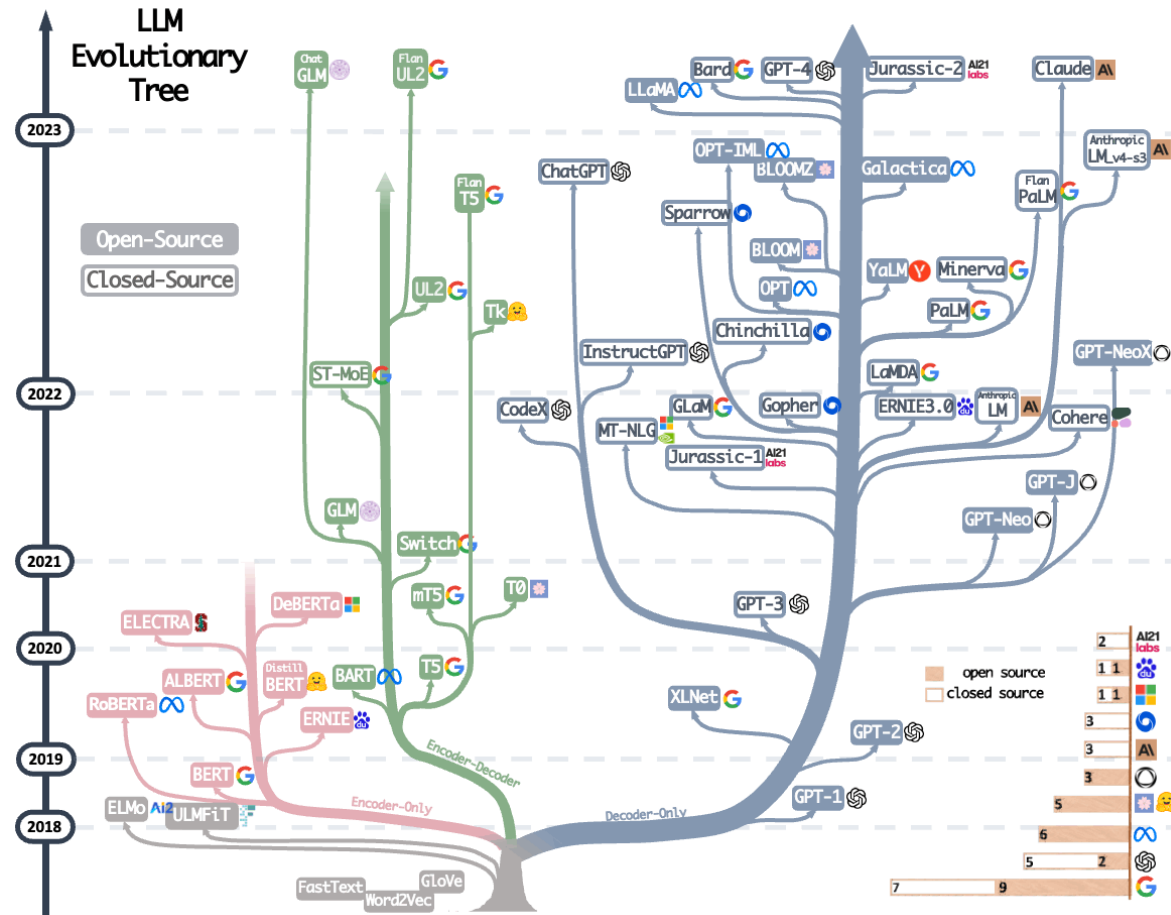
Pre-training: first training a model on one task or dataset, then using the parameters or model from this training to train another model on a different task or dataset

Fine-tuning: the procedure of re-training a pre-trained language model using smaller, task-specific data

Prompt-tuning: adds a small number of tunable embeddings to an otherwise frozen model

In-Context learning: LLMs are prompted with instructions or demonstrations to solve a new task without any additional training

Emergent ability: An ability is emergent if it is not present in smaller models but is present in larger models. [Wei et al, 2022]



Source: <https://github.com/Hannibal046/Awesome-LLM>

Dialogue Pre-training



Dialog-Post: Multi-Level Self-Supervised Objectives and Hierarchical Model for Dialogue Post-Training
Zhenyu Zhang, Lei Shen, Yuming Zhao, Meng Chen, Xiaodong He
The 61st Annual Meeting of the Association for Computational Linguistics (ACL 2023)



POSPAN: Position-Constrained Span Masking for Language Model Pre-training
Zhenyu Zhang, Lei Shen, Yuming Zhao, Meng Chen, Xiaodong He
The 32nd ACM International Conference on Information and Knowledge Management (CIKM 2023)

Transformer is All You Need!!!

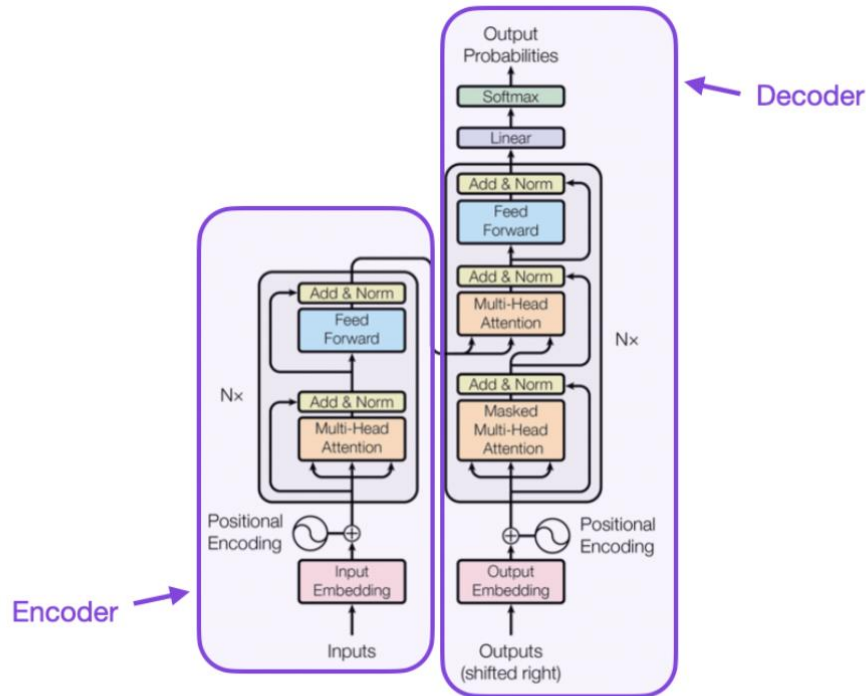
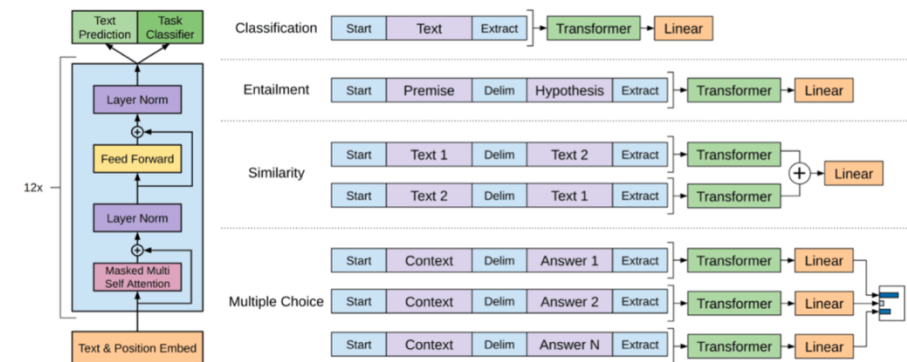


Figure 1: The Transformer - model architecture.

[Vaswani et al, 2017]

- The original transformer architecture consisting of an encoder- and decoder part. The internal core parts include the scaled dot product attention mechanism, multi-head attention blocks, and positional input encoding
- With the success of GPT series, decoder-style architecture and pretraining via next-word prediction become mainstream structure.

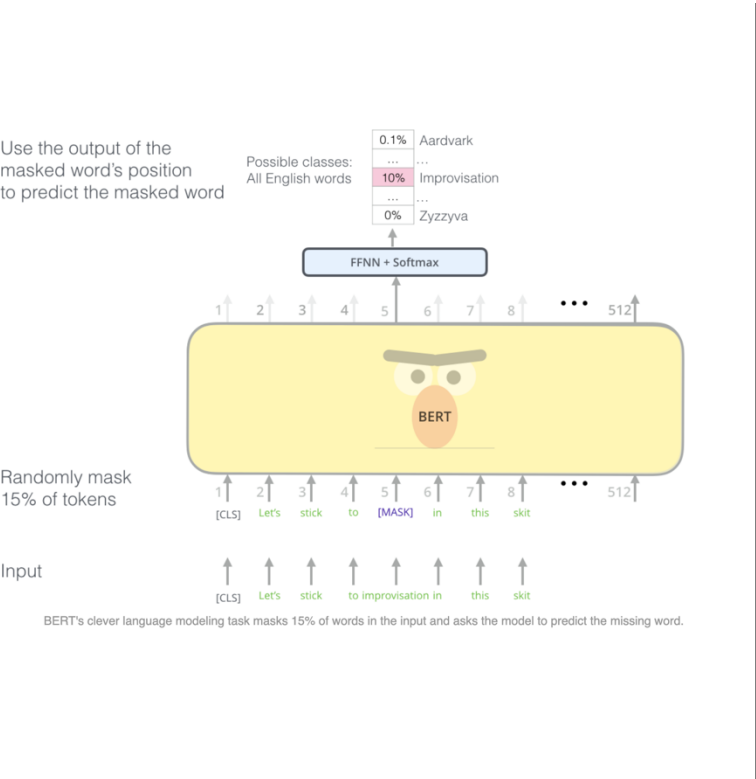
Decoder-style GPT model (originally for predictive modeling)



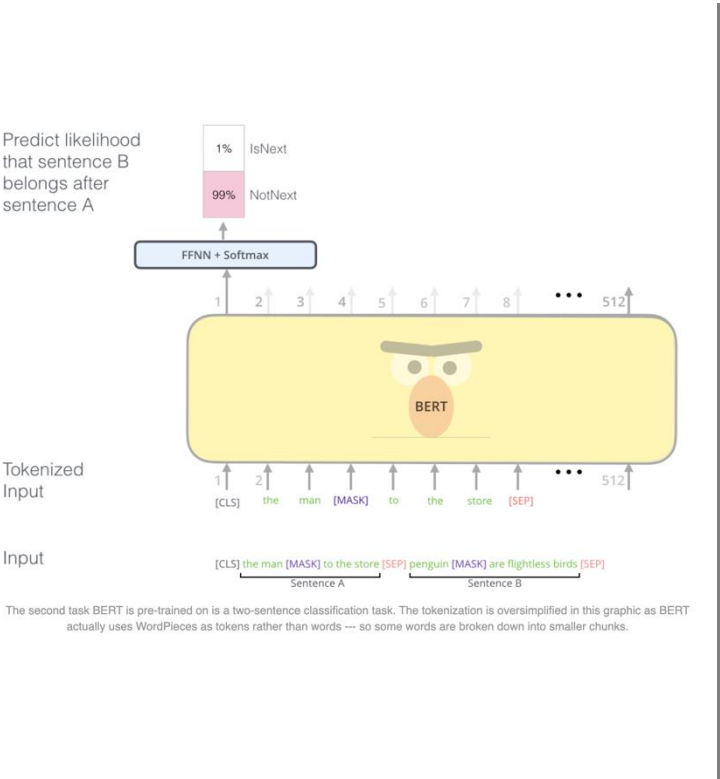
[Radford et al, 2018]

Self-supervised Learning for Pre-training

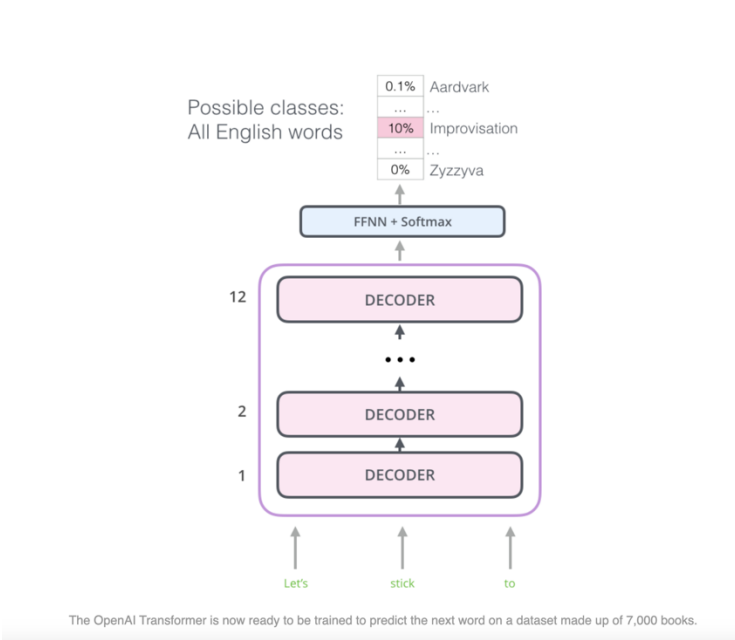
- Self-supervised learning: supervise using labels generated from the data without any manual or weak label sources



Masked Language Modeling (MLM)



Next Sentence Prediction (NSP)



Next Word Prediction (NWP)

Existing Drawbacks & Motivations

Characteristics of dialogues

- Hierarchical semantic structure (Serban et al., 2016; Xing et al., 2018; Zhang et al., 2019), i.e., dialogue → utterance → token
- Multi-facet attributes (See et al., 2019; Shen et al., 2021a), such as speaker-shift, content-relatedness, fact-awareness, and coherence



Motivations

- How can we improve our modeling of the hierarchical semantic relations in dialogues?
- Is it possible to design auxiliary pre-text tasks that capture the multi-faceted attributes of dialogues?
- With the classic token/span masking method, are we overlooking anything?

HSSA: Hierarchical Segment-wise Self-Attention Network

- HSSA model contains several layers, and each layer is a block consisting of inner-segment self-attention, intersegment self-attention, segment updater, and feedforward sub-layers
- HSSA can reduce the memory cost from $O(n^2)$ to $O(nB + (\frac{n}{B})^2 + n)$

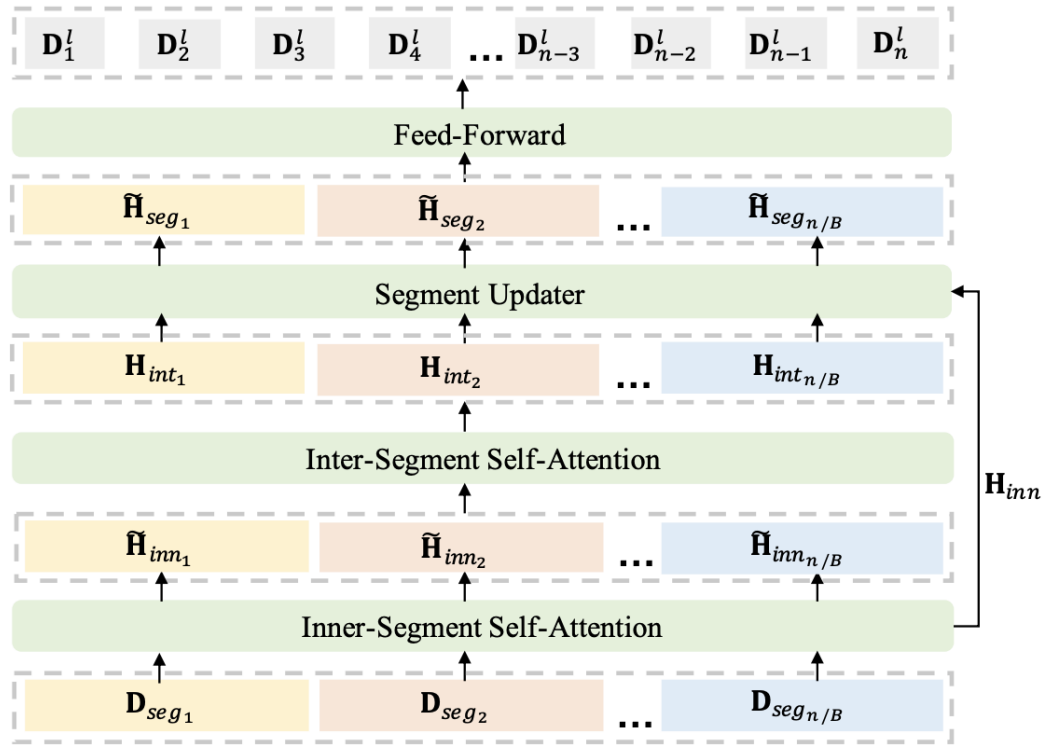


Figure 2: Overview of a HSSA layer.

$$\mathbf{H}_{inn_i} = \text{SA}(\mathbf{D}_{seg_i}) \in \mathbb{R}^{B \times \tilde{d}}$$

$$\text{Agg}(\mathbf{H}_{inn_i}) = \frac{1}{\sum_{j=1}^B e^{\mathbf{M}_j}} \sum_{j=1}^B \mathbf{H}_{inn_{i,j}} * e^{\mathbf{M}_j},$$

$$\alpha_{ij} = \text{softmax}\left(\frac{\text{Agg}(\mathbf{H}_{inn_i}) \mathbf{H}_{inn_{i,j}}^T}{\sqrt{d}}\right), j \in [1, B],$$

$$\tilde{\mathbf{H}}_{inn_i} = \mathbf{W}_p \left(\sum_{j=1}^B \mathbf{H}_{inn_{i,j}} * \alpha_{ij} \right)^T + \mathbf{b}_p,$$

$$\tilde{\mathbf{H}}_{inn} = [\tilde{\mathbf{H}}_{inn_1}, \tilde{\mathbf{H}}_{inn_2}, \dots, \tilde{\mathbf{H}}_{inn_{n/B}}],$$

$$\mathbf{H}_{int} = \text{SA}(\tilde{\mathbf{H}}_{inn})$$

$$\tilde{\mathbf{H}}_{seg_{i,j}} = \beta_{i,j} * \mathbf{H}_{int_i} + \mathbf{H}_{inn_{i,j}},$$

$$\beta_{i,j} = \text{softmax}\left(\frac{\mathbf{H}_{inn_{i,j}} \mathbf{H}_{int_i}^T}{\sqrt{d}}\right), j \in [1, B].$$

SSOs: Multi-level self-supervised objectives

$$\mathcal{L} = \mathcal{L}_{DSM} + \mathcal{L}_{DRM} + \mathcal{L}_{DUC} + \mathcal{L}_{DUP} + \mathcal{L}_{DCL}$$

- We design five multilevel SSOs to post-train the dialogue encoder, which consist of two token-level SSOs, one utterance-level SSO, and two dialogue-level SSOs
- Apply the popular continuous multi-task learning (CMTL) framework for model training, which can pre-train models with multitask objectives efficiently and prevent knowledge forgetting of previous tasks when training with the current task objective(s)

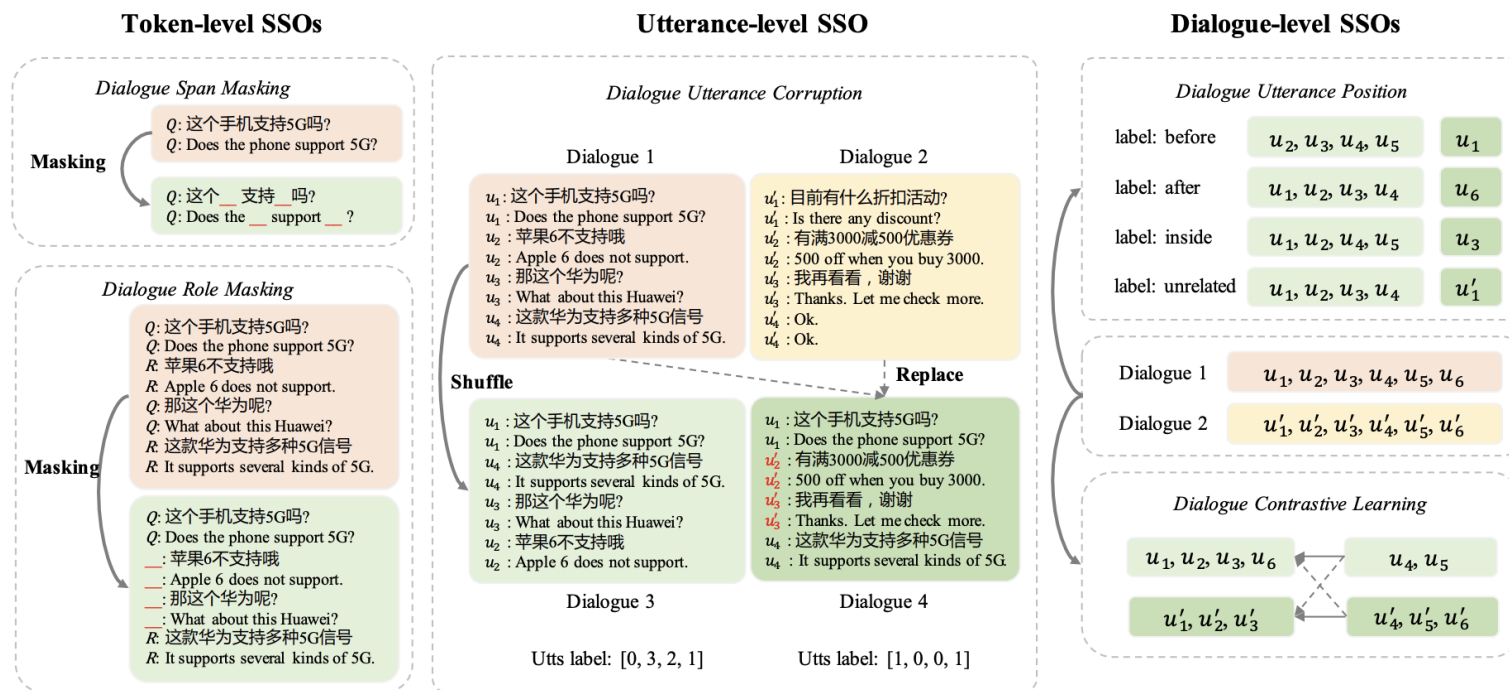


Figure 1: Illustration of multi-level SSOs in DIALOG-POST. Q and R represent speaker roles. u_i represents utterance. The utterance/dialogue in green color represents the corrupted utterance/dialogue.

POSPAN: Position-Constrained Span Masking

- Existing span masking only considers span length with some discrete distributions, while the dependencies among spans are ignored
- We present POSPAN, a general framework to allow diverse position-constrained span masking strategies via the combination of span length distribution and position constraint distribution

- Case 1:** There are barely any dependency or semantic relationship between S_i and S_j , i.e., we can predict S_i and S_j independently without knowing each other.
- Case 2:** $S_i \rightarrow S_j$, i.e., S_i is the premise of S_j . When S_i appears, S_j will appear most of the time.
- Case 3:** $S_j \rightarrow S_i$, i.e., S_j is the premise of S_i .

$$P(S_i, S_j | R_{ij}) = \frac{P(R_{ij} | S_i, S_j) * P(S_i, S_j)}{P(R_{ij})}, \quad (1)$$

$$\log P(S_i, S_j | R_{ij}) \propto \underbrace{\log P(R_{ij} | S_i, S_j)}_{\textcircled{1}} + \underbrace{\log P(S_i, S_j)}_{\textcircled{2}},$$

$$\sum_{i,j} \log P(S_i, S_j) = \frac{(M-1) \log P(S_1, S_2, \dots, S_M)}{2}$$

$$\propto \sum_{i=1}^M \log P(S_i). \quad (2)$$

$\mathcal{L}_S \rightarrow \max(\mathbb{E}[\log P(S_i | \text{len}_i)])$, where

$$\mathbb{E}[\log P(S_i | \text{len}_i)] = \mathbb{E}_{\text{len}_i \sim F_M} \left(\sum_{l=0}^{\text{len}_i-1} \log P(x_{i+l}) \right).$$

$$P(R_{ij} | d) = P(R_{ij} | x_{\text{pos}_i-1}, \dots, x_{\text{pos}_j+\text{len}_j})$$

$$= \frac{P(x_{\text{pos}_i-1}, \dots, x_{\text{pos}_j+\text{len}_j} | R_{ij}) * P(R_{ij})}{P(x_{\text{pos}_i-1}, \dots, x_{\text{pos}_j+\text{len}_j})}$$

$$= P(R_{ij}) * \frac{P(S_i, S_j | R_{ij}) * \prod_{k=\text{pos}_j-d}^{\text{pos}_j-1} P(x_k | R_{ij})}{P(S_i, S_j) * \prod_{k=\text{pos}_j-d}^{\text{pos}_j-1} P(x_k)} \quad (3)$$

$$= P(R_{ij} | S_i, S_j) * \frac{\prod_{k=\text{pos}_j-d}^{\text{pos}_j-1} P(x_k | R_{ij})}{\prod_{k=\text{pos}_j-d}^{\text{pos}_j-1} P(x_k)}$$

where $d \sim F_D$.

$$P(R_{ij} | S_i, S_j) \propto P(R_{ij} | d). \quad (4)$$

Finally, the pre-training with masked language modeling can be decomposed into two losses:

$$\mathcal{L} = \mathcal{L}_R + \mathcal{L}_S, \quad (5)$$

$$\mathcal{L}_R \rightarrow \max(\mathbb{E}[\log P(R_{ij} | F_D)]),$$

Experiments

- **Datasets**

- Pre-training: JDDC (Chen et al., 2020) and ECD (Zhang et al., 2018)
- POSPAN: 9 public NLU tasks

- **Evaluation**

- Dialogue Representation Evaluation: SR & STS
- Dialogue Understanding Evaluation: IC, Senti, CtxQ, CtxR

Task	Class	Metric	Train	Test
J/D-STC	-	Corr.	-	2,000
J/SR	-	MAP/MRR	-	6,970
E/D-STC	-	Corr.	-	1,000
E/SR	-	MAP/MRR	-	4,243
IC	30	F1	4.7K	988
Senti	7	ACC	2.7K	342
CtxQ	2	AUC	4.1K	620
CtxR	2	AUC	4K	593

Table 3: Details of evaluation tasks. “J” and “E” represent JDDC and ECD.

Method	JDDC			ECD		
	Corr.	MAP	MRR	Corr.	MAP	MRR
BERT (Devlin et al., 2019)	72.60	53.03	66.99	74.26	59.32	76.89
ELECTRA (Clark et al., 2020)	71.05	52.21	66.30	73.07	56.07	76.14
ERNIE (Sun et al., 2019, 2020)	72.73	52.96	66.79	74.29	59.11	76.87
UMS (Whang et al., 2021)	74.69	56.39	70.33	75.23	60.99	78.06
TOD-BERT (Wu et al., 2020)	78.43	60.15	74.32	80.17	65.78	80.22
PLATO (Bao et al., 2020b, 2021)	73.48	53.86	68.00	74.65	60.52	77.16
DialBERT (Zhang et al., 2021)	76.55	58.83	72.09	78.65	62.23	78.64
DomainAP (Wu et al., 2021)	76.54	59.27	72.36	78.99	62.85	79.08
DialCSE (Liu et al., 2021)	81.22	68.02	79.52	83.94	69.32	81.20
DIALOG-POST-BERT	82.78	69.91	79.83	83.96	71.78	81.78
DIALOG-POST	82.90	69.95	79.87	83.91	71.65	81.72

Table 2: Evaluation results on semantic retrieval (SR) and dialogue-based semantic textual similarity (D-STC) tasks.

Method	IC	Senti	CtxQ	CtxR	Average
BERT (Devlin et al., 2019)	86.0±0.3	71.9±1.8	87.9±1.1	80.0±0.9	81.5
ELECTRA (Clark et al., 2020)	87.4±0.5	72.5±0.6	88.9±0.5	81.7±1.5	82.6
ERNIE (Sun et al., 2019, 2020)	87.2±0.3	73.4±1.0	89.2±1.2	82.9±0.4	83.2
UMS (Whang et al., 2021)	86.8±0.3	71.2±1.0	88.8±0.8	84.0±0.1	82.7
TOD-BERT (Wu et al., 2020)	87.4±0.9	74.8±1.2	87.8±0.7	82.8±0.5	83.2
PLATO (Bao et al., 2020b, 2021)	86.5±0.4	73.1±0.1	88.9±0.4	82.2±0.4	82.7
DialBERT (Zhang et al., 2021)	88.5±0.4	73.5±0.5	87.5±0.4	81.9±0.5	82.8
DomainAP (Wu et al., 2021)	87.9±0.4	73.8±0.5	89.1±0.4	83.7±0.2	83.6
DialCSE (Liu et al., 2021)	86.8±0.3	73.6±0.5	90.7±0.8	85.6±0.2	84.2
DIALOG-POST-BERT	91.3±0.7	78.3±0.9	92.0±0.6	87.3±0.8	87.2
DIALOG-POST	91.8±0.5	78.1±0.5	92.4±0.7	87.9±0.5	87.5

Table 4: Evaluation results on dialogue understanding tasks (all with significance value $p < 0.05$).

Ablation Study

Ablation of HSSA

- We stack 10 layers of HSSA blocks and 2 layers of Transformer blocks, the last 2 Transformer layers are devised to capture the full dialogue semantics based on the global self-attention (SA) mechanism. Here, we first replace the last 2 Transformer layers with 2 HSSA layers (denoted as “w/o trs”)
- The performance of Senti becomes slightly better with all HSSA blocks. Since the input of Senti task is an utterance without context, it is possible that the 12-layer HSSA focusing on the local attention has some advantages

Model	JDDC			ECD		
	Corr.	MAP	MRR	Corr	MAP	MRR
HSSA	82.90	69.95	79.87	83.91	71.65	81.72
w/o trs	78.92	65.40	76.31	79.84	68.25	78.86
w/o updater	74.20	65.61	74.35	75.67	67.33	77.85
w/o H_{int}	58.75	49.83	65.74	56.92	59.86	74.99
w/o H_{inn}	45.97	48.64	63.22	29.65	49.57	69.02

Table 9: Experimental results of HSSA Ablation Study on all dialogue representation tasks.

Model	IC	Senti	CtxQ	CtxR	Average
HSSA	91.8	78.1	92.4	87.9	87.5
w/o trs	91.0	78.5	91.2	87.2	87.0
w/o updater	88.6	77.6	90.5	86.5	85.8
w/o H_{int}	86.8	75.2	87.9	82.7	83.2
w/o H_{inn}	76.6	68.9	82.4	73.0	75.2

Table 10: Experimental results of HSSA Ablation Study on all dialogue understanding tasks.

Ablation of SSOs

- We remove one training objective each time while keeping the remaining four, each training objective contributes to the overall performance to some extent, indicating the multi-level SSOs are complementary
- DCL brings the most benefits, which implies the effectiveness of DCL on capturing the content-relatedness of context-context pairs

Method	JDDC			ECD		
	Corr.	MAP	MRR	Corr.	MAP	MRR
DIALOG-POST	82.90	69.95	79.87	83.91	71.65	81.72
w/o DRM	82.84	69.93	79.90	83.95	71.64	81.72
w/o DSM	82.76	69.16	78.65	83.62	71.69	81.24
w/o DUC	81.96	69.25	79.69	83.91	71.64	81.72
w/o DUP	81.75	68.99	79.13	83.58	71.18	81.71
w/o DCL	77.98	61.21	75.33	80.16	67.35	79.06

Table 11: Experimental results of SSOs Ablation Study on all dialogue representation tasks.

Method	IC	Senti	CtxQ	CtxR	Average
DIALOG-POST	91.8	78.1	92.4	87.9	87.5
w/o DRM	91.2	77.9	91.8	87.0	87.0
w/o DSM	91.0	77.4	90.9	86.9	86.6
w/o DUC	89.7	77.4	90.3	85.1	85.6
w/o DUP	91.0	77.8	91.2	86.7	86.7
w/o DCL	89.0	77.0	89.6	86.5	85.5

Table 12: Experimental results of SSOs Ablation Study on all dialogue understanding tasks.

Experimental Results of POSPAN

- All post-training models bring further improvements compared to the strong baseline DeBERTaV3, which shows the effectiveness of post-training
- Compared with single-token masking, all span-level masking methods yield substantial improvements, indicating the advantage of span-level masking on capturing the critical semantics of language.
- POSPAN obtained the best performance across different tasks, which demonstrates the superiority and necessity of position constraint for span masking

Notation	Distribution	F_M	F_D
<i>Pois</i>	Poisson	$\lambda = 4$	$\lambda = 5$
<i>Norm</i>	Normal	$\sigma=1, \mu=4$	$\sigma=1, \mu=5$
<i>Geo</i>	Geometric	$p=0.2$	$p=0.1$
<i>Rand</i>	Uniform	$a=1, b=5$	$a=4, b=6$

Table 1: Hyper-parameters of different distributions. We tune hyper-parameters of the distributions via grid search and find the best settings.

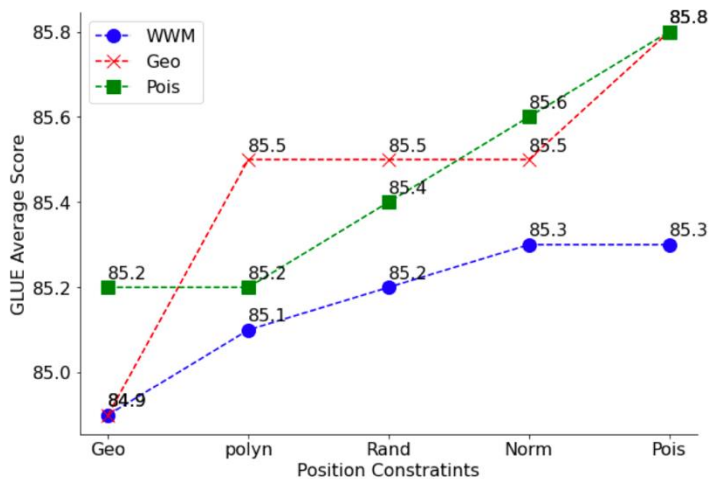


Figure 1: The model performance of POSPAN with different position constraints (x -axis).

Method	CoNLL	MNLI(m/mm)	MRPC	QNLI	BoolQ	COPA	ReCoRD	SQuAD	RACE
DeBERTaV3 (He et al., 2021a)	94.9	88.1/88.3	87.0	92.4	80.1	70.3	56.5/44.6	84.8/82.0	52.0
MLM (Devlin et al., 2019)	95.3	88.2/88.5	88.4	92.5	80.5	70.9	56.3/44.9	84.8/82.1	52.1
Fixed	95.3	88.2/88.6	88.2	92.8	80.6	72.9	56.5/44.9	84.7/82.2	52.2
N-gram (Cui et al., 2020)	95.3	88.2/88.5	88.6	93.0	81.2	73.5	56.7/45.2	84.9/82.2	52.4
WWM (Cui et al., 2021)	95.2	88.2/88.5	88.0	92.7	80.8	71.8	56.4/44.7	84.8/82.2	52.3
Geo (Joshi et al., 2020)	95.7	88.5/88.7	88.9	93.1	81.3	73.2	56.8/45.1	85.0/82.5	52.5
Pois (Lewis et al., 2020)	95.6	88.4/88.7	87.5	93.0	81.0	73.9	56.7/45.1	85.1/82.5	52.3
POSPAN(WWM-Norm)	95.5	88.3/88.5	88.5	93.1	80.9	73.3	56.9/45.0	84.8/82.3	52.5
POSPAN(Geo-Pois)	95.9	88.8/89.0	89.2	93.4	81.6	75.7	57.3/45.6	85.4/82.5	52.8
POSPAN(Pois-Pois)	95.8	88.9/89.3	88.2	93.2	81.9	75.6	57.1/45.3	85.6/82.7	53.1

Table 2: Experimental results of POSPAN. POSPAN(*Geo-Pois*) denotes $F_M \sim Geo$ and $F_D \sim Pois$. CoNLL and SQuAD represent ConNLL 2003 and SQuAD v2.0. MNLI (m/mm) represents the two versions of MNLI, MNLI-matched and MNLI-mismatched. The complete evaluation results are reported in Appendix A.4.

Method	MNLI (m/mm)	QNLI	QQP	MRPC	RTE	CoLA	SST-2	STS-B	Avg.
BERT-base (Devlin et al., 2019)	74.4/75.5	85.3	81.6	78.3	63.1	58.1	91.4	88.7	77.3
MLM (Devlin et al., 2019)	74.8/75.8	86.3	83.1	77.2	64.1	57.9	91.6	88.3	77.7
Fixed	74.6/75.6	86.4	83.2	80.6	62.8	59.5	92.1	89.9	78.3
N-gram (Cui et al., 2020)	74.5/75.2	86.4	83.2	80.4	64.0	59.3	91.8	90.3	78.4
WWM (Cui et al., 2021)	74.5/75.7	85.9	82.6	77.6	63.4	61.6	92.0	90.2	78.2
Geo (Joshi et al., 2020)	74.9/75.8	86.1	82.5	81.0	64.4	60.2	91.5	90.4	78.5
Pois (Lewis et al., 2020)	75.2/75.5	86.9	82.9	81.2	63.9	60.8	92.1	90.0	78.7
POSPAN(WWM-Norm)	76.0/ 76.9	87.4	83.5	78.5	65.9	60.8	93.1	90.5	79.2
POSPAN(Geo-Pois)	75.9/76.2	87.2	83.9	82.4	64.3	59.9	92.1	91.2	79.2
POSPAN(Pois-Pois)	76.2/76.7	87.3	84.1	82.4	66.1	59.4	92.9	91.4	79.6

Table 7: Experimental results of POSPAN in GLUE with BERT as base model. POSPAN(*Geo-Pois*) denotes $F_M \sim Geo$ and $F_D \sim Pois$. MNLI (m/mm) represents the two versions of MNLI, MNLI-matched and MNLI-mismatched.

Pre-sales E-commerce Chatbot

JD AlphaSales

京小智 专业版

- 问答管理
 - 问答知识管理
 - 关键词管理
 - 商品属性管理
 - 答案时效管理
 - 智能问答预测
 - 多店知识库同步
 - 接待模式设置 **NEW**
- 特色场景 **NEW**
 - 活动咨询
 - 商品比较
 - 图片应答
 - 物流咨询
 - 截图回复
 - 发票申请 **NEW**
- 问答数据
 - 机器优先数据
 - 辅助人工数据
- 智能推荐
 - 商品推荐

新老客福利：免费领京小智专业版

点击领取

目前使用版本：**专业版** 2023-02-22日到期，剩余**295**天 [前往续费](#)

目前使用增值服务：**全链跟单** 2024-02-28日到期

机器接待流量包 预计还可使用 37838 天 199838836(剩) / 200000000(总)	辅助坐席包 预计还可使用 295 天 199431(未使用) / 200001(总)	咚咚流量包 预计还可使用 5736 天 197732111(剩) / 200000500(总)
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价值月报

- 智能应答
 - 节省人力 **59.02**人
 - 平均响应时长减少 **9.2s**
 - 30秒应答率提升 **4.36%**
- 全链跟单

店铺诊断

上次更新时间：2022-05-02 [查看更多诊断](#)

问题识别率 74.88% 比上个周期： -0.74%	答案覆盖率 83.3% 比上个周期： +0.6%	纯机转人工率 43.63% 比上个周期： +0.66%	辅助回复率 19.93% 比上个周期： +3.13%
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无需打开机器人开关即可测试

需针对商品咨询，咨询前请先发送sku [发送](#)

测试窗 单条语料测试 批量测试

测试模式： 机器优先模式 辅助人工模式

当前会话ID：c9f1612de7bd40178b45517e0e324ef4

你好

命中知识 [聊天互动>问候类>问候](#)

当前答案 您好，我在的哦~有什么问题建议您可以直接描述一下的呢

答案编辑

可以七天无理由退货么

命中知识 [售后咨询>退货相关>退货](#)

当前答案 请您放心，本店所售商品都是严格按照国家三包政策，在商品完好无损、商品包装和配件等完好齐全的情况下可享受签收7天内无理由退货，30天产品性能故障问题退换货的呢。

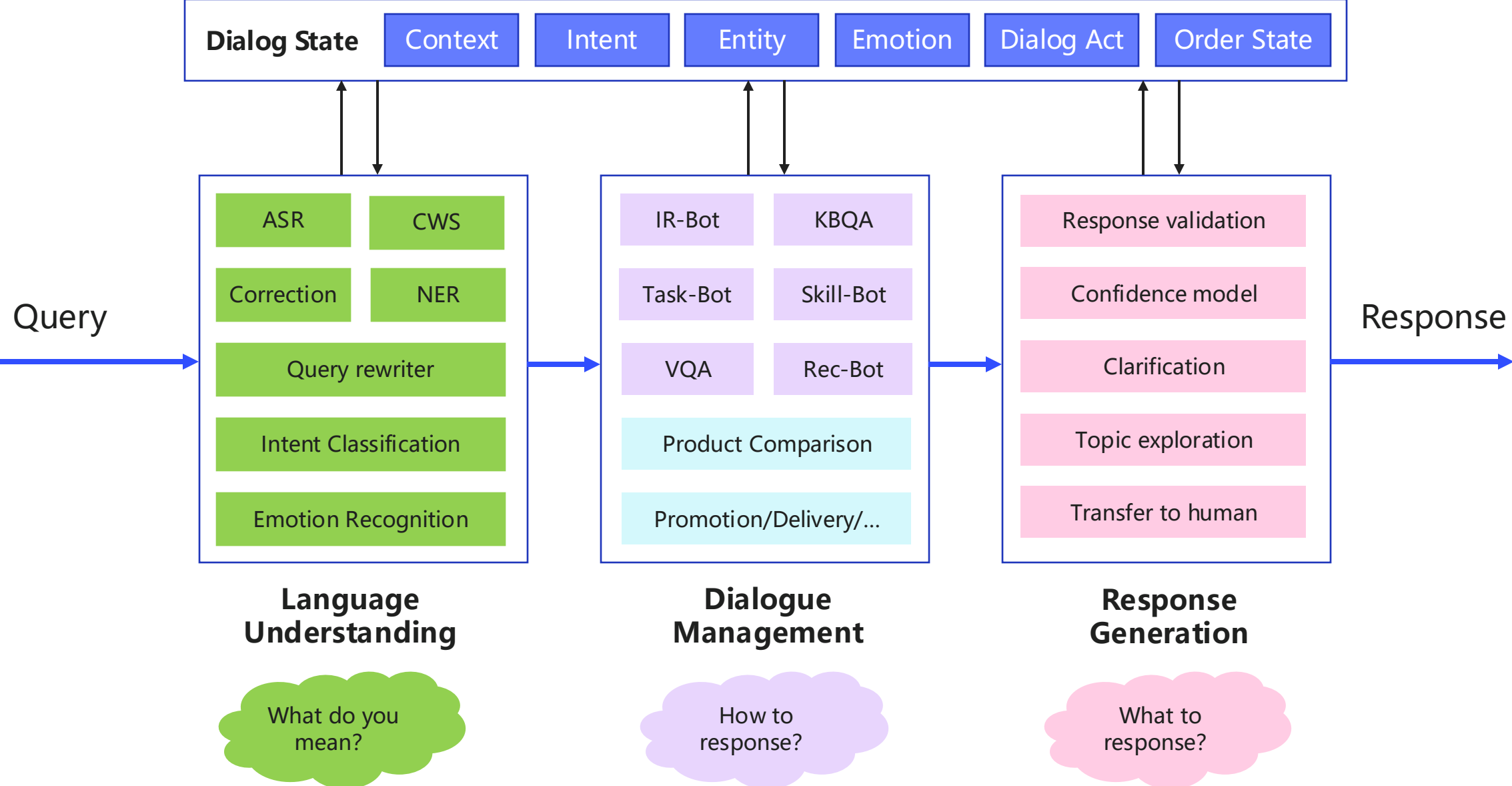
答案编辑

最近有啥优惠么

命中知识 [活动咨询>活动及规则>商品价格及到手价](#)

当前答案 您好，请在下方选择您所咨询的商品哦

Architecture of Dialogue System



Main Features

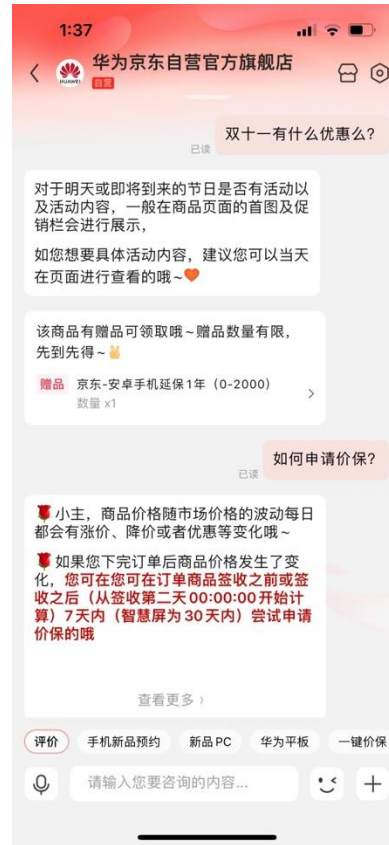
Product Comparison



Selling Point Generation



Promotion Checking



Attribute Inquiry

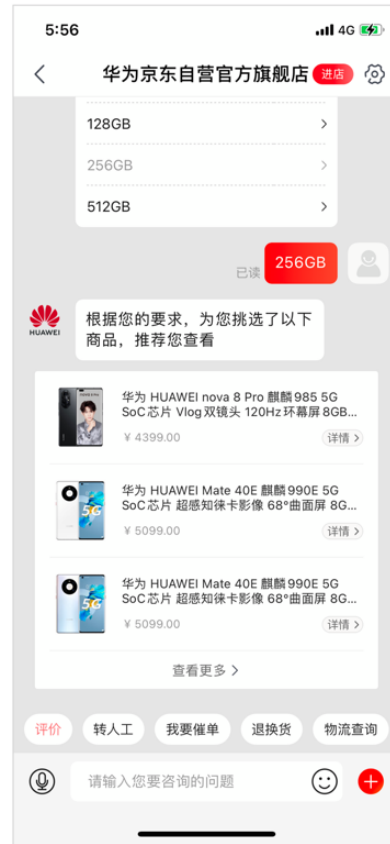


Policy Inquiry



Main Features (Cont.)

Conversational Recommendation




Multimodal Conversation




Financial Home Loan Chatbot

LLM-based AI Home Loan






ANZ AMP Commonwealth Bank Instantly compare thousands of home loans from 100+ leading lenders** HSBC ING Westpac



Discover Your Perfect Home Loan with Ease

Navigating home loans has never been simpler.

Our intelligent chatbot is here to guide you through the complex world of home loans. It's designed to understand your needs, answer your questions, and help you find the right home loan for you.

-  **Instant, Personalised Advice** Get real-time, tailored recommendations based on your needs.
-  **First of its kind AI home loan assistant** Experience the innovation in home loan assistance.
-  **Saves time and effort in home loan research** Skip the hassle and let our chatbot do the work.

got. Ready to kick off with a few key questions? Could you please share your tentative plan with us?

I want to buy a new home

That's great! It's always exciting to plan for a new home. Are you planning for your first home purchase, if I may ask?

Yes

It's fantastic that you're planning to purchase your first home. The next thing I'd like to understand is your loan purpose. Are you seeking to be the owner occupier, or is this an investment?

Owner Occupier

Great, thanks for the clarification. Now, could you please tell me your preferred repayment type? Would it be principal and interest or interest only?

Choose from the below, or type a question here...

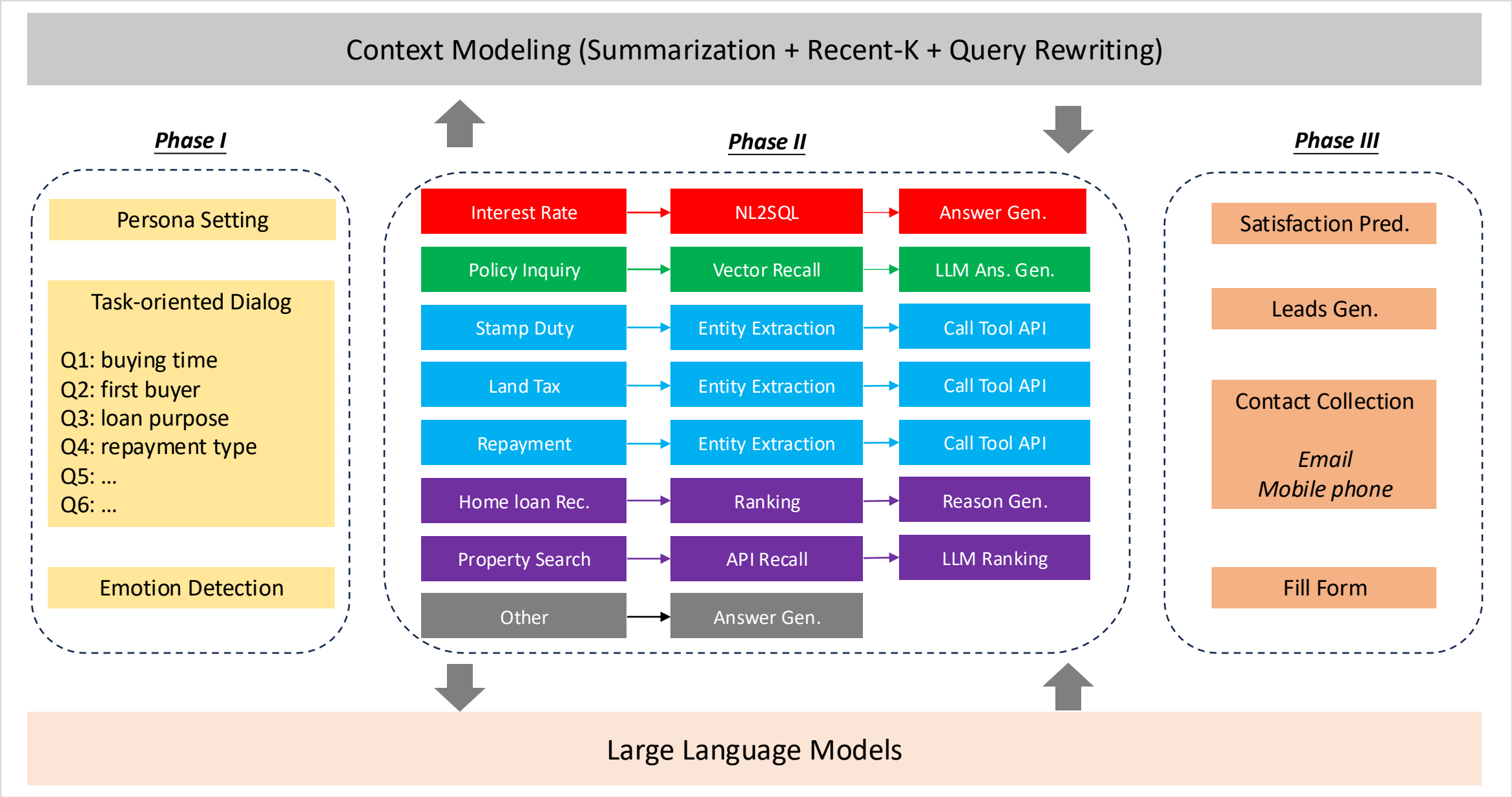
Interest Only

Principal and Interest

What's the difference?

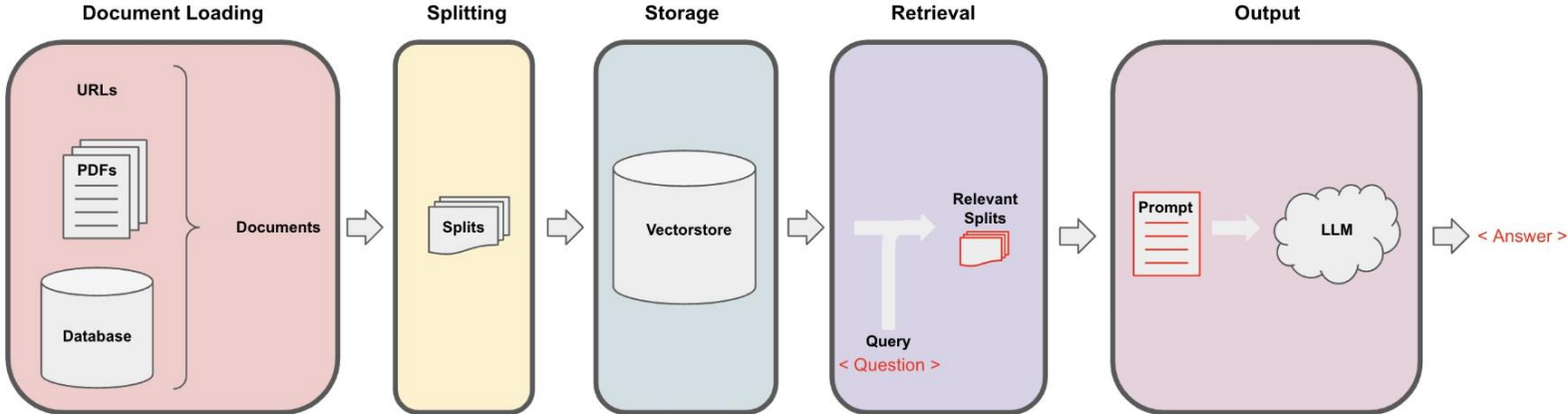
Have a try: <https://www.yephome.com.au/chat>

Architecture of AI Home Loan

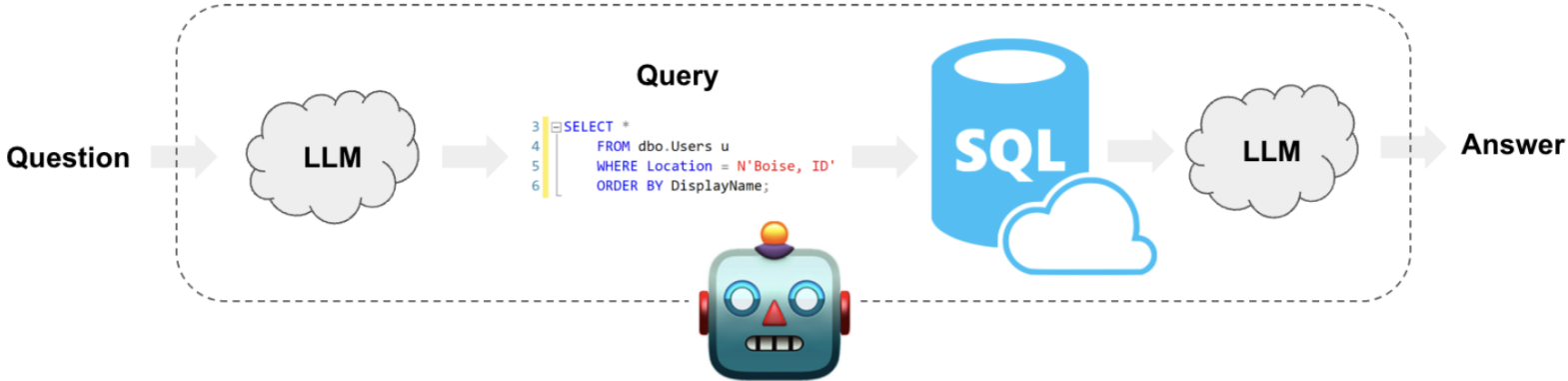


Core Engine: RAG & NL2SQL

Question & Answering over unstructured document



Question & Answering over structured database



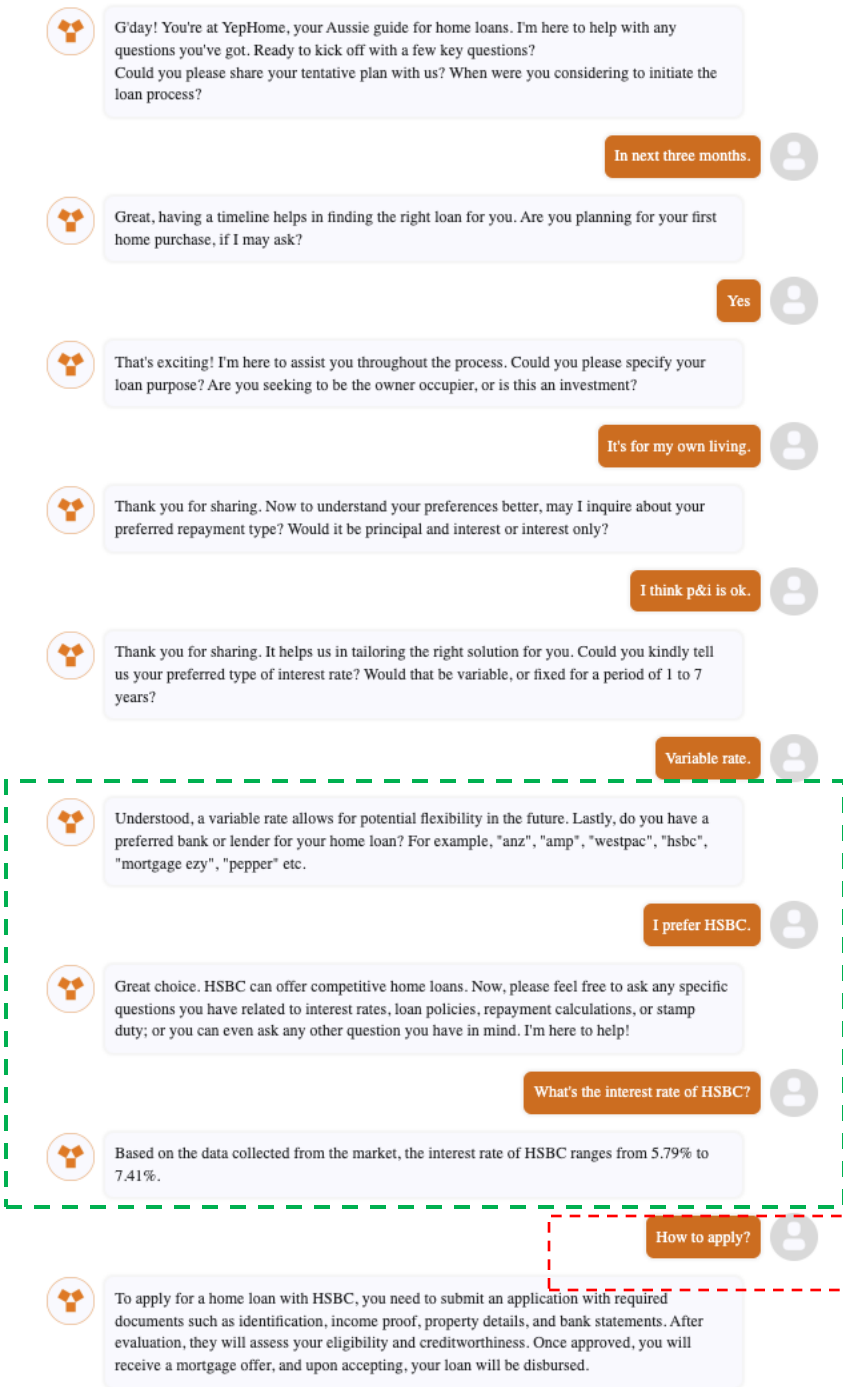
Context Modeling

Summarization:

The dialogue is between a user and a home loan assistant. The assistant asks the user about their tentative plan to initiate the loan process in the next three months. The user confirms they are planning for their first home purchase. The assistant asks about the loan purpose, and the user states it is for their own living. The assistant then asks about the preferred repayment type, and the user chooses principal and interest. The assistant asks about the preferred interest rate type, and the user chooses a variable rate. Lastly, the user states a preference for HSBC as the bank or lender. The assistant offers to answer any specific questions the user may have and provides a general interest rate range for HSBC.

Recent-K utterances

Query rewriting: What is the procedure for home loan application with HSBC?



Case Study 1: Calculation

Question: How much stamp duty should I pay for 1.5 million house in Melbourne, I'm Chinese.

GPT-4: \$255,170 🎁

Anthropic: \$122,500 🎁

YepGPT: \$202,500 😎

How much stamp duty should I pay for 1.5 million house in Melbourne, I'm Chinese

Stamp duty rates can vary and are subject to change, so it's always a good idea to consult the most current information from the State Revenue Office of Victoria or a financial advisor for the most accurate and personalized advice. As of my last update in January 2022, the stamp duty for a residential property in Victoria was calculated on a sliding scale based on the property value.

Here's a simplified example of how stamp duty could be calculated for a \$1.5 million house:

- Up to \$25,000: 14% of dutiable value
- Over \$25,000 to \$130,000: \$350 plus 2.4% of dutiable value in excess of \$25,000
- Over \$130,000 to \$960,000: \$2,870 plus 6% of dutiable value in excess of \$130,000
- Over \$960,000: 5.5% of the dutiable value

For a \$1,500,000 house:

- \$2,870 for the first \$130,000
- 6% of (\$960,000 - \$130,000) = \$49,800
- 5.5% of \$1,500,000 = \$82,500

Adding these together: \$2,870 + \$49,800 + \$82,500 = \$135,170

This is a simplified example and actual rates can be different. Additional surcharges or exemptions may also apply, especially if you are a foreign purchaser. As of my last update, foreign purchasers were subject to an additional 8% surcharge on top of the regular stamp duty in Victoria.

Therefore, with the foreign purchaser surcharge, you might have an additional \$1,500,000 * 0.08 = \$120,000.

So, the total stamp duty could be around \$135,170 + \$120,000 = \$255,170.

Hallucination!

How much stamp duty should I pay for 1.5 million house in Melbourne, I'm Chinese

Here are the key factors that determine the amount of stamp duty on a \$1.5 million house purchase in Melbourne, Australia for a Chinese buyer:

- Stamp duty rates in Victoria are progressive, meaning the rate increases for properties over certain price thresholds. For a \$1.5 million property, the stamp duty rate is 5.5%.
- There is an additional 3% stamp duty surcharge that applies to foreign buyers in Victoria, including buyers from China.
- As a Chinese buyer, you would not be eligible for the First Home Owner Grant which can provide stamp duty savings for first time Australian resident buyers.
- The total stamp duty payable would be:

Standard stamp duty:
First \$1 million at 5% = \$50,000
Remaining \$500,000 at 5.5% = \$27,500
Total standard stamp duty = \$77,500

Plus foreign buyer surcharge at 3% of \$1.5 million = \$45,000

Total stamp duty payable = \$77,500 + \$45,000 = \$122,500

So in summary, as a Chinese buyer purchasing a \$1.5 million house in Melbourne, you can expect to pay total stamp duty of \$122,500. Let me know if you need any clarification or have additional questions!

Copy Retry

How much stamp duty should I pay for 1.5 million house in Melbourne, I'm Chinese

As a first home buyer, you may be eligible for certain concessions or exemptions on stamp duty. In Victoria (VIC), the stamp duty for a \$1.5 million house in Melbourne would be \$202,500. However, if you are a first home buyer, as well as a foreigner, there may be different rules and additional requirements that you need to consider. I recommend consulting with a professional mortgage advisor who can provide you with accurate and up-to-date information based on your specific circumstances.

State/Territory of the property *
VIC

Property Value *
\$ 1500000

Property Type
Primary Residence Investment Property

First Home Buyer? New Property? Foreign purchasers?
Yes No Yes No Yes No

Estimated Price
Stamp Duty A\$202,500

Case Study 2: Recommendation

Question: Which home loan is the top pick in Australia?

GPT-4: No answer 🙅

Anthropic: No answer 🙅

YepGPT: Done! 😎

Web Browsing ⓘ

Which home loan is the top pick in Australia?

Finished browsing

I am unable to fetch the latest information at the moment due to a technical glitch. However, I can provide some guidance on how to find the top pick for home loans in Australia. Here's how you might proceed:

- Comparison Websites:** Utilize comparison websites that compare different home loans available in Australia. Websites like Finder, Canstar, or RateCity can provide a good starting point.
- Financial Institutions:** Look at the home loan offerings from reputable financial institutions in Australia like Commonwealth Bank, Westpac, ANZ, or NAB. They often have competitive rates and terms.
- Customer Reviews and Ratings:** Check customer reviews and ratings to get an idea of the satisfaction level of different home loan customers.
- Consult a Financial Advisor:** If possible, consult with a financial advisor who can provide personalized advice based on your financial situation.
- Check the Australian Securities and Investments Commission (ASIC) website:** They have resources on understanding home loans and may have recommendations or information on reputable lenders.

Remember, the "top pick" may vary from person to person based on individual circumstances such as credit score, down payment, and other financial factors.

Which home loan is the top pick in Australia? M

There is no single "top pick" for home loans in Australia, as the best loan depends on an individual's specific circumstances and needs. However, here are some tips on choosing the best home loan in Australia:

- Compare interest rates and fees from multiple lenders. The major banks like CBA, Westpac, ANZ and NAB often have competitive rates, but it's worth checking smaller lenders too. Online comparison sites can make this easier.
- Consider both variable and fixed rate loans. Variable rates are usually lower but move with the market, fixed rates provide certainty. Split loans offer both options.
- Look at features like offset accounts, extra repayments and redraw facilities. These can help you save on interest.
- Evaluate the loan term. Longer terms (up to 30 years) mean lower repayments but higher interest costs over time.
- Think about loans packaged with features like a credit card or discounts on insurance. The cheapest headline rate may not offer the best package.
- Factor in approval criteria and application process. An easy application and faster approval could be worth paying a slightly higher rate.
- Consider using a mortgage broker. They can help compare loans and lenders for your situation.

So in summary, do your research to find the loan with the right mix of competitive rate, features and service for your personal needs and financial situation. There is no definitively best home loan for everyone.

AI Copy Retry

Not accurate!

Which home loan is the top pick in Australia? ⓘ

Based on the current information, I would like to recommend the following Top 3 home loan products:

- BCU OMG! Home Loan - LVR ≤ 60% (Owner Occupier, P&I)**
Interest Rate: 5.64%
Monthly Repayment: \$5766.04
Pros: Low interest rate, Redraw facility available
Cons: No offset account.
- Homestar Star Gold (Owner Occupier, P&I)**
Interest Rate: 5.69%
Monthly Repayment: \$5797.67
Pros: Very low variable interest rate, No ongoing fees, 100% offset account
Cons: Requires a very large deposit
- Bendigo Bank Express Variable Home Loan - (Owner Occupier, P&I)**
Interest Rate: 5.72%
Monthly Repayment: \$5816.68
Pros: Borrowers can use as little as a 10% deposit, Loan amount from \$5,000 to \$3 million, Extra repayments available, Full offset account available for variable loans, partial offset for fixed loans
Cons: Monthly ongoing fee of \$10, Exit fees and switching fees applicable, Late payment fee of \$35, You are not eligible for this loan if you're buying outside a capital city or major regional centre

The above monthly repayments are calculated based on 30 years loan term and a \$1000000 loan amount.

Case Study 3: Info-Seeking

Question: What's the lowest interest rate of Westpac for home loan?

GPT-4: 6.09% 🤔

Anthropic: N/A 🙏

YepGPT: \$5.79% 😎

The screenshot shows a search engine results page. The top result is from a source labeled 'Finished browsing'. The text of the result states: "The lowest interest rate for a home loan from Westpac, as of the information available, is offered through their Flexi First Option Home Loan, which has a special offer rate of 6.09% per annum (p.a.) with a comparison rate of 6.42% p.a. This rate includes a discount of 1.74% p.a. for the first two years from the loan settlement date, which then reverts to a 1.34% p.a. discount thereafter. This special offer is applicable for new loans with a loan-to-value ratio (LVR) of up to 70%¹. It's important to note that other sources have mentioned slightly different rates, possibly due to different periods or specific loan conditions. For instance, Finder mentioned a similar rate of 6.09% p.a. for the Westpac Flexi First Option Home Loan², while RateCity mentioned rates from Westpac starting from 6.29% p.a.³. There's also a mention of a special Westpac home loan product known as the 'Greater Choices' Home Loan which offers an interest-free period for five years, but this information comes from a New Zealand based source and may not apply to Australian customers⁴. For the most accurate and updated information, it's advisable to check Westpac's official website or contact Westpac directly."

Not accurate!

The screenshot shows an AI chat interface. The user asks: "What's the lowest interest rate of Westpac for home loan?". The AI responds: "Unfortunately I do not have enough context to provide the specific home loan interest rate for Westpac bank. Banks often have variable interest rates that depend on factors like the type of home loan, loan amount, customer's credit profile and market conditions. However, here are a few suggestions that may help:"

- Check Westpac's website or speak to a Westpac representative to inquire about current interest rates for different home loan products they offer. They can provide rates based on your specific loan requirements.
- Look at comparison sites like Canstar or Finder to see Westpac's published variable and fixed interest rates for home loans relative to other major banks. This can give you an idea of their competitive positioning.
- The Reserve Bank of Australia (RBA) cash rate gives a benchmark of general interest rate trends. Westpac's variable home loan rates will move up or down with the cash rate. The current cash rate is 0.10% as of October 2022.
- Consider getting quotes from multiple lenders. Interest rates can vary significantly, so shopping around is wise.
- Ask Westpac if they can provide a discount or package deal on interest rates for certain home loans or for customers meeting certain criteria. This may lower the rate.

The specific lowest rate will depend on your personal situation and the home loan product that suits you. I'd recommend consulting Westpac directly to get the most accurate and up-to-date rate for your particular home loan requirements. Let me know if you need any other details!

The screenshot shows a chat interface. The user asks: "What's the lowest interest rate of Westpac for home loan?". The AI responds: "Based on the data collected from the market, the lowest interest rate of Westpac for home loan is 5.79%."

How about the comparison rate?

Based on the data collected from the market, the comparison rate is 6.14%.

What's the largest lvr?

Based on the data collected from the market, the largest Loan to Value Ratio (LVR) is 95%.

* This screenshot was made two weeks ago



Chatbot

Enter Your Description

Audio

• Stop recording

Clear

Submit

Take-aways

- The core components of language understanding can be effectively reconstructed based on Large Language Models (LLMs), which significantly simplifies the design process of dialogue systems.
- Efficiently incorporating external domain knowledge into LLMs can mitigate the hallucination problem to a certain degree.
- A multimodal dialogue system, enhanced by an AI avatar, speech interaction, and LLMs, holds immense commercial potential for the future.

Q&A

Thanks!

Email: chenmengdx@gmail.com

Home page: <https://chenmengdx.github.io/>

Visit: <https://www.yepai.com.au/>

