Curse of bilinguality: Evaluating monolingual and bilingual language models on Chinese linguistic benchmarks

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Abstract

We investigate cross-lingual transfer effects in large language models (LLMs) trained on two high-resource languages, English and Chinese. Four monolingual Chinese and four bilingual English–Chinese models are evaluated on two Chinese linguistic benchmarks. The monolingual models consistently outperform the bilingual ones on 12 out of 55 tasks, while the reverse is true for only 4 tasks, highlighting the prevalence of negative (rather than positive) transfer from English to Chinese. Additionally, we carry out a feature attribution analysis in a monolingual and a bilingual model, showing that the differences in their performance may be explained by more predictable attribution patterns in the monolingual model. Our findings have implications for the ongoing effort of training bilingual LLMs.

1 Introduction

In multilingual NLP, cross-lingual transfer is traditionally described in positive terms. For example, a model's performance in low-resource languages can be improved by leveraging transfer from high-resource languages. At the same time, adding low-resource languages to the training data may cause a model to perform worse in high-resource languages due to the *negative* cross-lingual transfer, a phenomenon known as the curse of multilinguality (Conneau et al., 2020). Despite the abundance of studies that address this problem (Blevins et al., 2024; Wang et al., 2020; Pfeiffer et al., 2022, etc.), they primarily focus on multilingual LLMs trained on a variety of languages with very unbalanced amounts of data per language.

What happens, however, when a model is trained on exactly two high-resource languages? English and (Mandarin) Chinese are the two languages with the largest amounts of data available for training, and the recent years have seen a surge in the development of LLMs for both languages. While a few Chinese models are monolingual (e.g., Sun et al., 2021; Zhang et al., 2021; Zeng et al., 2021), most others are either bilingual (i.e., trained on a mix of English and Chinese data: Bai et al., 2023; Yang et al., 2023; Young et al., 2024) or multilingual (see a survey by Huang et al., 2025). While bilingual and multilingual models perform well on some English benchmarks (e.g., Zeng et al., 2024), it is unclear whether they always outperform their monolingual counterparts in Chinese linguistic tasks.

In this paper, we study cross-lingual transfer effects in bilingual Chinese–English LLMs. We evaluate four monolingual Chinese models and four bilingual Chinese–English models on two commonly used Chinese linguistic benchmarks. For a number of paradigms in these benchmarks, the monolingual models (including the relatively small monolingual Chinese BERT) consistently outperform the bilingual ones, indicating negative transfer from English to Chinese. We then present an interpretability analysis using feature attribution methods on two selected models, showing that the bilingual model may be worse at capturing the relations between words in the target sentences than the monolingual one.[1]

2 Method

2.1 Models

We consider a diverse set of pretrained transformer-based LLMs. While there are many *multilingual* LLMs that support both Chinese and English, we focus on the cross-lingual transfer specifically from English to Chinese and only consider bilingual (not multilingual) models, to eliminate possible influences from other languages. Specifically, we select four monolingual Chinese and four bilingual Chinese–English models, based on their perfor-

[1]Our code is available at https://github.com/YuwenZhou99/zh_transfer.

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Model	# param.	Languages
ERNIE	10B	Chinese
CPM	2.6B	Chinese
PANGU	2.6B	Chinese
BERT	0.11B	Chinese
QWEN	14B	Chinese–English
BAICHUAN	7B	Chinese–English
YI	6B	Chinese–English
CHATGLM	6B	Chinese–English

Table 1: Monolingual and bilingual models we consider.

mance on common benchmarks and their number of parameters, to cover a variety of model sizes while staying within the limits of our available computational resources. The models and their number of parameters are listed in Table 1. Note that the monolingual models (except ERNIE) generally have fewer parameters, potentially giving the bilingual models an advantage thanks to their size. In all cases, we use HuggingFace implementations.

The monolingual Chinese models include (1) Ernie-3.0 (Sun et al., 2021), which combines a masked and an autoregressive training objectives and is trained on 4TB of both textual data and structured knowledge graphs, (2) CPM-Large (Zhang et al., 2021), an autoregressive model trained on 100GB of Chinese text, (3) Pangu-alpha-2.6B (Zeng et al., 2021), the smallest of the Pangu family of autoregressive models, also trained on 100GB of Chinese text, and (4) Chinese BERT (Devlin et al., 2019), a much smaller model considered for reference.

The bilingual Chinese–English models include (1) Qwen (Bai et al., 2023), the base Qwen-family model trained on 3 trillion tokens, (2) Baichuan-7B (Baichuan, 2023), the smaller of the first-generation Baichuan models, trained on 1.2 trillion tokens, (3) Yi-6B (Young et al., 2024), a Yi-family model trained on a 3.1 trillion high-quality Chinese–English tokens, and (4) ChatGLM3-6B (Zeng et al., 2024), a GLM-series model optimized for Chinese question answering and dialogue.

2.2 Benchmarks

We evaluate our models on two commonly used linguistic benchmarks of minimal pairs in Chinese: CLiMP (Xiang et al., 2021) and SLING (Song et al., 2022). CLiMP is the Chinese adaptation of the English BLiMP benchmark (Warstadt et al., 2020). It has been criticized for its use of translations that do not naturally reflect Chinese linguistic phenomena (Song et al., 2022). To address this limitation, the second benchmark, SLING, derives its minimal pairs from naturally occurring annotated Chinese sentences and applies syntactic and lexical transformations specifically designed for Chinese grammar, offering a more linguistically grounded evaluation framework. Together, these two benchmarks contain 18 Chinese linguistic phenomena sub-divided into 55 paradigms with more than 50k minimal pairs of sentences.

In most of the paradigms, each minimal pair consists of one grammatical and one ungrammatical sentence. For example, in the SLING *Alternative Question* paradigm, the sentence with the 吗 *(ma)* particle is always ungrammatical, since this particle can only be used in yes–no (but not alternative) questions:

(1) 她们 是 飞行员 还是 制片人 [吗*] ?
they be pilot or producer [Q*] ?
'Are they pilots or producers?'

However, in eight SLING *Anaphor* paradigms (*baseline female/male, baseline cl female/male, baseline cl man female/male, baseline cl men female/male*), both sentences are grammatical. For example, in the SLING *baseline female* paradigm:

(2) 女队员 攻击了 [她 / 他] 。
female.team.member attacked [she / he] .
'The female team member attacked her/him.'

A model's score in these paradigms, therefore, indicates its preference towards one or the other sentence (i.e., bias) rather than accuracy.

2.3 Evaluation

We use the standard method of evaluating the models on minimal pairs. In each pair, sentence perplexity (or pseudo-perplexity, for masked models) values are computed, and the sentence with a lower perplexity is taken to reflect the model's preference. This preference is then compared to the ground-truth data, and the model's accuracy for each paradigm (or bias, in case of the eight SLING paradigms mentioned above) is computed.

For each paradigm, we then compare the resulting values of the 4 monolingual models against those of the 4 bilingual models. In case of positive cross-lingual transfer, one could expect the bilingual models to show higher accuracy values. However, if we observe that for some of the paradigms

Paradigm	Monolingual models				Bilingual models			
	ERNIE	CPM	PANGU	BERT	QWEN	BAICHUAN	YI	CHATGLM
Coverb								
—"— with	82.3	61.7	73.5	84.7	**86.2**	**84.9**	**84.8**	**84.8**
Verb complement								
—"— res adj	59.7	25.9	59.3	87.6	**92.1**	**95.2**	**91.1**	**90.9**
—"— res verb	**92.8**	**96.7**	**90.1**	**96.2**	61.2	65.7	64.2	61.4
Alternative Question								
haishi ma	**94.6**	**85.8**	10.0	**93.1**	9.8	26.6	6.5	**64.0**
Anaphor (Gender)								
baseline female	**92.9**	**89.8**	**95.9**	**86.7**	32.1	66.2	70.3	67.1
Anaphor (Number)								
baseline cl female	**99.5**	**77.9**	0.0	**99.4**	10.1	16.2	29.4	**40.7**
baseline cl male	**99.9**	**75.1**	0.0	**99.6**	26.0	42.9	**47.6**	45.3
baseline cl men female	**99.5**	**88.8**	0.0	**99.4**	5.9	9.7	25.3	**34.8**
baseline cl men male	**100**	**87.6**	0.0	**100**	17.9	38.0	38.9	**43.2**
baseline men female	**99.3**	**51.8**	0.0	**98.0**	6.7	9.4	28.7	**41.4**
cl men self female	**98.3**	**96.2**	0.0	**100**	87.5	**95.4**	84.0	77.9
cl self female	**99.2**	**88.8**	0.0	**99.9**	74.8	**82.8**	62.4	70.2
Definiteness Effect								
every	**96.2**	**92.5**	87.7	**94.6**	**88.0**	69.2	58.7	84.9
Polarity Item								
even wh	85.8	42.3	47.7	52.4	**97.7**	**98.4**	**96.9**	**98.0**
more or less	**98.3**	**98.6**	**97.6**	**97.9**	86.2	96.8	93.3	79.5
Relative Clause								
rc resumptive pronoun	54.8	18.6	11.8	42.7	**64.3**	**77.8**	**68.1**	**60.8**

Table 2: The models' performance (accuracy scores, in percentages) in selected CLiMP (top part) and SLING (bottom part) paradigms. In each row (paradigm), four highest scores are highlighted in bold.

the monolingual models (which are also generally smaller) consistently outperform the bilingual ones, this can be seen as evidence of negative cross-lingual transfer.

The evaluations and analyses were conducted on a single Nvidia V100 GPU with 32GB memory, over a total duration of 30 hours. We provide the results below, followed by a feature attribution analysis.

3 Results and analyses

3.1 Model performance

For the majority of paradigms in both benchmarks, we do not observe consistent differences between monolingual and bilingual models' scores (see Tables A1–A2 in the Appendix). This result is expected, due to the large variation in model architectures, number of parameters, and the amounts of data they are trained on.

At the same time, from Table 2 we see that 3 (out of 16) CLiMP paradigms and 4 (out of 39) SLING paradigms yield very consistent differences between bilingual and monolingual model scores, and for 9 more SLING paradigms the differences are consistent except the low performance of the monolingual PANGU model. Adding up these numbers, we observe reliable differences in 16 out of the 55 paradigms (29%).

To compute how likely this result could occur by chance, we use bootstrapping, randomly sampling two sets of four scores (in the range between 0.00 and 100.00) 55 times to see whether we obtain the result like ours or more extreme. Specifically, for a sample of 55 cases $\times$ 2 sets $\times$ 4 scores, we check whether in at least 7 cases all 4 scores in one set are greater than all 4 scores in the other set, and in at least 9 more cases 3 scores from one set are greater than all 4 scores in the other set. Having repeated the sampling process 100k times, we estimate the probability of obtaining a result like ours (or more extreme) to be 0.069%, a very low value.

Importantly, out of the 16 paradigms with consistent differences, bilingual models show higher scores only in 4 paradigms, indicating either positive cross-lingual transfer or the bilingual models' advantage due to their larger sizes. The monolingual models are better in 12 paradigms, indicating negative transfer. In other words, these results suggest that negative cross-lingual transfer is common in bilingual language models. In other words, having a large amount of English text alongside a large amount of Chinese text in the training data does not necessarily help – and may even hinder – model performance on Chinese tasks.

We have shown that monolingual models (including the much smaller BERT) score better than bilingual models on a number of linguistic paradigms. We now turn to analyzing the profiles of models' feature attribution to answer the question: Can the different scores of monolingual vs. bilingual models be explained by the differences in how well they capture the key relations between words in target sentences?

3.2 Feature attribution analysis

We investigate how the important words from the left context affect the generation of the target word in the sentences from the two evaluation benchmarks. Consider again example (1) from Section 2.2. After reading the last word 制片人 ('producer'), a human speaker should note the presence of the word 还是 ('or'), which indicates an alternative question and calls for the end of sentence rather than the 吗 (*ma*) particle. Analogously, in the context of LLMs, after decoding 制片人 ('producer'), to generate an appropriate token, the model should focus on the token 还是 ('or'), which we consider to be the keyword. This keyword suggests that the end of sentence (in this case, a question mark) is a more appropriate token to generate than the 吗 (*ma*) particle. Consequently, we expect a (monolingual) model with higher performance on the target paradigm (represented by this sentence) to assign a higher importance value to the keyword (here: 还是, 'or') during the generation of a target token (here: question mark), compared to a (bilingual) model with lower performance.

To test this hypothesis, we use the Inseq interpretability toolkit (Sarti et al., 2023), which is well suited for gradient-based feature attribution analysis. Given the left context, we constrain a model to generate the next target token from the grammatical sentence (the question mark in the example above).

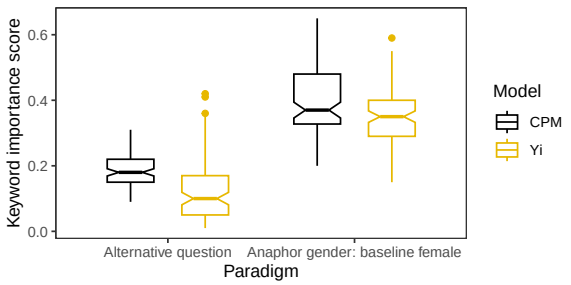

Figure 1: Keyword importance scores of the monolingual CPM and bilingual YI model in two paradigms.

We then use the integrated gradients method to compute the distribution of importance scores for all preceding tokens and extract the (normalized) score for the keyword (还是, 'or', in the example above). Finally, we compare the scores for a monolingual and a bilingual model.

We focus on one monolingual (CPM) and one bilingual model (YI), thanks to their Inseq support. Furthermore, we only consider two SLING paradigms (*Anaphor gender: baseline female* and *Alternative question: haishi ma*), as the rest were either incompatible with left-to-right processing (i.e., generating the correct target token would require right sentence context) or yielded tokenization patterns of the keyword and/or the target token that were different across the two models (CPM and YI), which would generate multiple scores per word and possibly render the comparison unfair. For each paradigm, we consider the first 100 minimal pairs and only use the grammatical sentence from each pair. For both models, we extract the keyword importance scores as described above (where the keyword is always 女, 'female', for *Anaphor gender: baseline female*, and 还是, 'or', for *Alternative question: haishi ma*). We compare the average importance scores and test whether there are statistically significant differences using the Wilcoxon signed-rank test (Wilcoxon, 1992) while correcting for false discovery rate (Benjamini and Hochberg, 1995).

From Figure 1, we see that in both paradigms the monolingual model yields higher keyword importance scores than the bilingual one. Our statistical tests confirm that the differences are significant, with both $p < .001$. This suggests that the monolingual CPM model better captures the relations between the keyword and the target token, which can explain its higher performance on a number of paradigms compared to the bilingual YI model.

4 Conclusion

We have evaluated four monolingual Chinese and four bilingual Chinese–English models on two Chinese linguistic benchmarks. Across 55 test tasks, we observe consistent performance differences between monolingual and bilingual models on 16 tasks – despite their smaller sizes, monolingual models perform better on 12 and worse only on 4 tasks. This result suggests that bilingual Chinese–English models may suffer from negative cross-lingual transfer. It extends prior findings on negative transfer in *multilingual* models (Chang et al., 2024) to a bilingual setting where both languages are high-resource and well-represented in training data. Our feature attribution analysis suggests that monolingual models' higher scores may stem from the fact that they better capture the key relations between words in sentences, compared to bilingual models. Our findings have implications for the ongoing effort of training bilingual LLMs on high-resource languages (e.g., Faysse et al., 2024; Zhang et al., 2024; Nikolich et al., 2024).

5 Limitations

This study only focuses on one language pair, English and Chinese, and only one direction of cross-lingual transfer (English to Chinese). It is unclear whether the results would generalize to other language pairs or to cross-lingual transfer from Chinese to English. We only consider a total of eight LLMs, all with 14B parameters or less, and the results may differ for larger models. The models we have compared differ on many dimensions, including architecture, size, objective, while ideally one would compare a monolingual and a bilingual model that only differ in their training data (one vs. two languages), to focus on the impact of bilingual training. The benchmarks we use, CLiMP and SLING, also come with limitations, namely they only evaluate the models' linguistic knowledge. Our interpretability analysis is further limited to only two paradigms, a constraint imposed by our method's requirement of left-to-right processing and by different tokenization schemes used in the models.

As we only evaluate existing models, we do not anticipate any risks related to misuse or negative application of the results presented in our study. However, our focus on the two languages with the highest amount of training data available contributes to the underexposure of lower-resource languages.

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A Appendix. Detailed evaluation scores

	Monolingual models				Bilingual models			
Paradigm	ERNIE	CPM	PANGU	BERT	QWEN	BAICHUAN	YI	CHATGLM
Anaphor agreement								
—"— gender	**85.6**	79.9	**92.6**	**86.2**	64.0	**86.5**	62.5	77.4
Binding								
—"— gender	**54.2**	51.3	**61.2**	50.8	50.0	**58.6**	51.2	**81.0**
ba construction								
—"—	**63.0**	57.8	19.3	**69.0**	62.4	**74.3**	**73.5**	60.7
Coverb								
—"— instrument	57.5	36.0	54.1	**91.1**	**80.8**	**79.5**	**80.5**	79.0
—"— with	82.3	61.7	73.5	84.7	**86.2**	**84.9**	**84.8**	**84.8**
NP head finality								
—"— clause	67.1	**86.5**	65.6	53.1	**80.3**	76.8	**80.6**	**80.2**
Classifier								
—"—	85.8	57.1	76.0	**95.6**	**92.4**	**90.2**	**90.2**	**93.8**
—"— adj	**87.8**	55.5	69.1	**93.2**	**91.8**	84.2	87.0	**88.1**
—"— clause	**84.3**	52.2	66.5	**90.0**	**89.3**	80.8	**84.3**	80.9
Filler gap								
—"— dependency	**87.3**	62.3	**91.9**	62.4	**71.1**	65.2	**70.3**	64.9
Passive								
—"— formal	**60.9**	47.0	**61.6**	**67.1**	53.8	50.3	49.2	**60.2**
Verb complement								
—"— direction	**96.2**	81.4	80.1	**93.0**	85.0	**91.8**	**86.1**	84.0
—"— duration	**92.8**	83.6	82.6	**90.2**	89.7	**92.8**	**94.2**	86.9
—"— frequency	**98.4**	48.8	**75.6**	**97.8**	19.9	25.4	32.6	**81.3**
—"— res adj	59.7	25.9	59.3	87.6	**92.1**	**95.2**	**91.1**	**90.9**
—"— res verb	**92.8**	**96.7**	**90.1**	**96.2**	61.2	65.7	61.4	64.2

Table A1: The models' performance (accuracy scores, in percentages) on CLiMP paradigms. Four highest scores in each paradigm are highlighted in boldface.

Paradigm	Monolingual models				Bilingual models			
	ERNIE	CPM	PANGU	BERT	QWEN	BAICHUAN	YI	CHATGLM
Alternative Question								
haishi ma	**94.6**	**85.8**	10.0	**93.1**	9.8	26.6	6.5	**64.0**
Anaphor (Gender)								
baseline female	**92.9**	**89.8**	**95.9**	**86.7**	32.1	66.2	70.3	67.1
baseline male	30.4	**53.8**	**100.0**	46.1	**48.9**	34.7	47.7	**64.5**
pp female	59.1	**95.2**	**98.6**	**87.0**	77.3	**96.3**	69.6	78.3
pp male	38.8	46.3	**99.9**	**76.0**	**79.8**	21.0	73.8	**74.2**
self female	92.8	66.4	**97.3**	93.3	**100.0**	**99.4**	**97.2**	90.4
self male	70.7	**86.7**	**100.0**	**88.4**	0.1	**75.0**	21.0	47.4
Anaphor (Number)								
baseline cl female	**99.5**	**77.9**	0.0	**99.4**	10.1	16.2	29.4	**40.7**
baseline cl male	**99.9**	**75.1**	0.0	**99.6**	26.0	42.9	**47.6**	45.3
baseline cl men female	**99.5**	**88.8**	0.0	**99.4**	5.9	9.7	25.3	**34.8**
baseline cl men male	**100.0**	**87.6**	0.0	**100.0**	17.9	38.0	38.9	**43.2**
baseline men female	**99.3**	**51.8**	0.0	**98.0**	6.7	9.4	28.7	**41.4**
baseline men male	**99.7**	**49.5**	0.1	**99.7**	20.2	40.4	41.1	**52.8**
cl men self female	**98.3**	**96.2**	0.0	**100.0**	87.5	**95.4**	84.0	77.9
cl men self male	**99.6**	97.1	0.0	**100.0**	**100.0**	**99.7**	98.8	93.3
cl self female	**99.2**	**88.8**	0.0	**99.9**	74.8	**82.8**	62.4	70.2
cl self male	**99.5**	85.8	0.1	**99.9**	**100.0**	96.3	**97.5**	92.2
manself female	**96.1**	67.4	0.0	**98.8**	**89.2**	**83.4**	80.5	61.3
manself male	98.3	61.1	0.0	**99.3**	**100.0**	**98.7**	**98.7**	94.3
Aspect								
temporal guo	**91.8**	79.7	72.4	**95.5**	81.3	82.8	**92.1**	**93.2**
temporal le	59.7	**78.8**	**73.9**	65.2	63.2	64.8	**70.5**	**74.6**
zai guo	**92.0**	78.6	65.4	**97.9**	77.5	**87.6**	**79.7**	79.4
zai no le	**64.8**	0.8	16.1	**85.2**	53.8	50.0	**57.0**	**59.4**
Classifier-Noun								
cl adj comp noun	**69.7**	55.6	53.4	70.7	**66.4**	**66.1**	**64.4**	63.0
cl adj comp noun v2	**85.5**	46.0	50.7	**87.5**	70.6	**71.9**	**76.8**	62.8
cl adj simple noun	**93.1**	58.9	77.1	**96.5**	92.8	**92.9**	**93.0**	79.8
cl comp noun	65.6	51.0	53.8	**69.8**	**62.9**	**68.8**	59.7	**67.6**
cl comp noun v2	**85.1**	45.2	55.5	**86.7**	70.2	70.0	**78.2**	**76.8**
cl simple noun	**96.1**	61.2	85.0	**98.5**	**96.0**	**95.1**	94.7	88.4
dem cl swap	**99.5**	52.5	85.7	**99.8**	88.7	**92.1**	**92.7**	88.7
Definiteness Effect								
demonstrative	**93.9**	48.3	49.3	**98.2**	**83.4**	58.0	44.5	**70.6**
every	**96.2**	**92.5**	87.7	**94.6**	**88.0**	69.2	58.7	84.9
Polarity Item								
any	85.2	**95.9**	**93.6**	65.8	82.9	**92.1**	77.2	**95.4**
even wh	85.8	42.3	47.7	52.4	**97.7**	**98.4**	**96.9**	**98.0**
more or less	**98.3**	**98.6**	**97.6**	**97.9**	86.2	96.8	93.3	79.5
Relative Clause								
rc resumptive noun	15.2	**82.1**	16.7	25.6	**37.9**	**25.8**	**31.4**	24.7
rc resumptive pronoun	54.8	18.6	11.8	42.7	**64.3**	**77.8**	**68.1**	**60.8**
Wh-fronting								
bare wh	**100.0**	96.6	99.7	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
mod wh	**100.0**	90.7	88.8	99.5	**100.0**	**100.0**	**99.9**	99.6

Table A2: The models' performance (accuracy scores, in percentages) on SLING paradigms. Four highest scores in each paradigm are highlighted in boldface.