

# Editing Across Languages

## A Survey of Multilingual Knowledge Editing

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### Motivation

LLMs are **static** and quickly become **outdated**.  
 Knowledge Editing **updates facts** efficiently **without retraining**.  
 An edit in one language should **generalize across languages**.  
 Multilingual Knowledge Editing ensures updates stay **aligned cross-lingually** while **preserving unrelated knowledge**.

### Example

**Outdated fact:** EMNLP is in Miami this year  
**Update:** EMNLP is in Suzhou this year

#### Multilingual Consistency:

¿Dónde se celebra EMNLP este año? → Suzhou  
 أين تقام فعاليات EMNLP هذا العام؟ ← سوتشو  
 今年的EMNLP会议在哪里举行? → 苏州

## Multilingual Knowledge Editing Methods

### Parameter Editing

Modify internal weights to update factual knowledge

- Provide Localized Updates
- Efficient Factual Editing
- Depends on Shared Internal Representations
- Limited Transfer
- Sensitive to Tokenization and Neuron Alignment

### Memory Based

Use In-context learning or an external memory without updating the model

- No parameter updates
- Inference time only
- Depends on language specific components
- Limited cross-lingual performance
- Scalability challenges

### Finetuning Based

Fine-tune models on Edit Descriptors

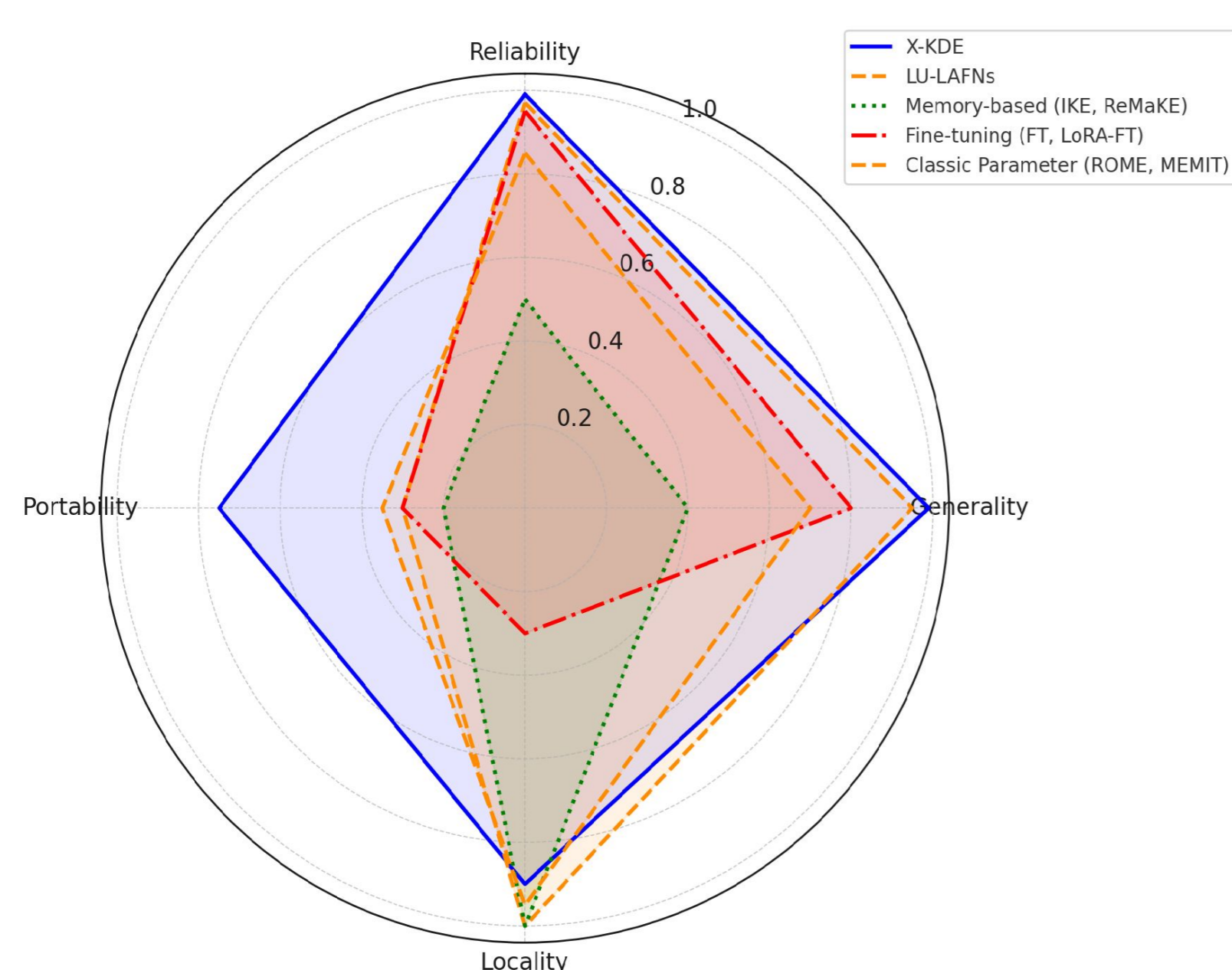
- Simple and Reliable
- Efficient Variants exist
- No guarantee of Cross-Lingual transfer
- Risk of Interference with unrelated knowledge
- Data and Design Demands

### Hypernetworks

Use an Auxiliary Hypernetwork to generate weight updates

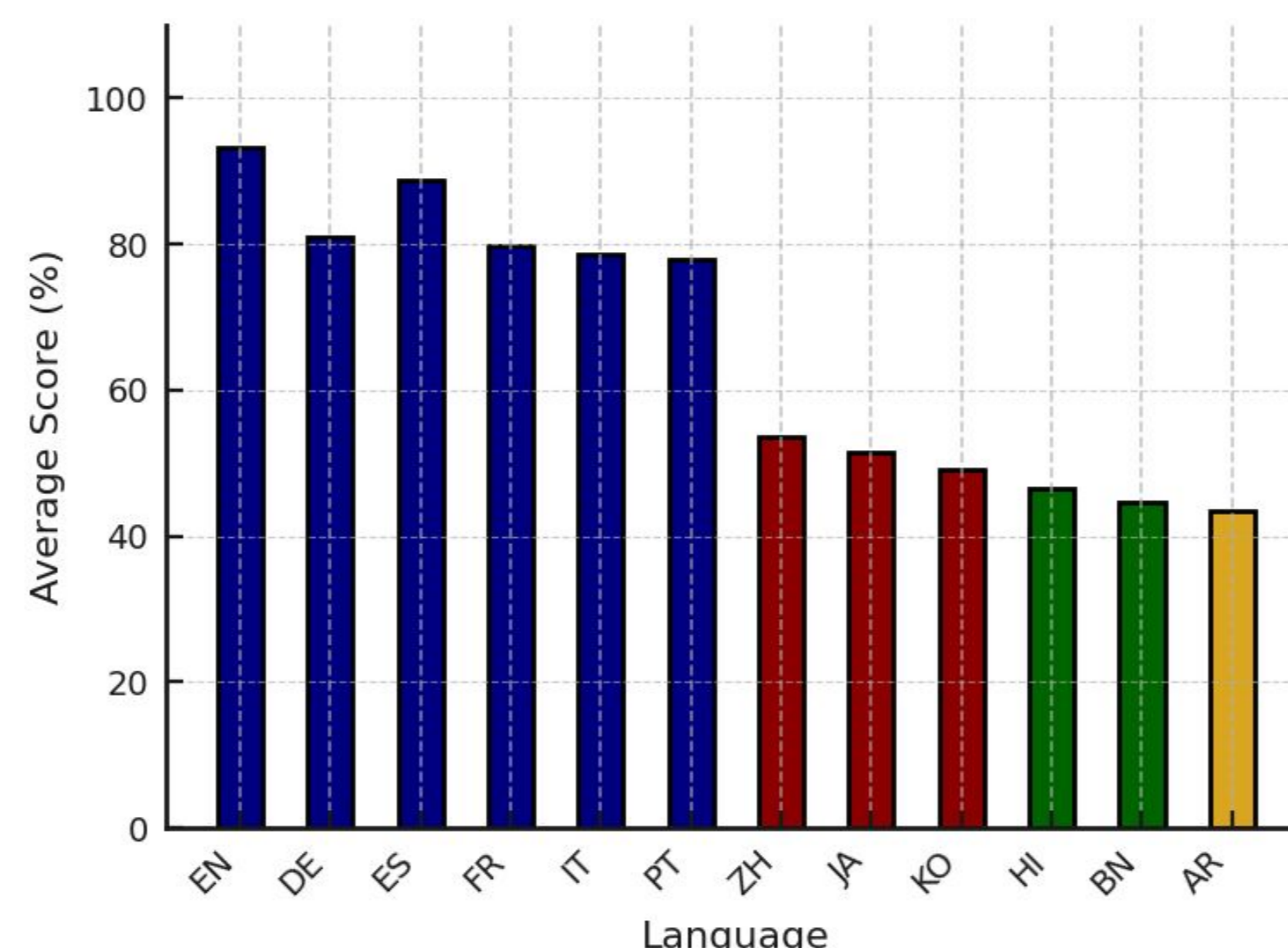
- Meta-Learning Capability
- Cross-Lingual Stability
- Data dependent
- Limited multilingual performance
- Language specific Constraints

## Findings



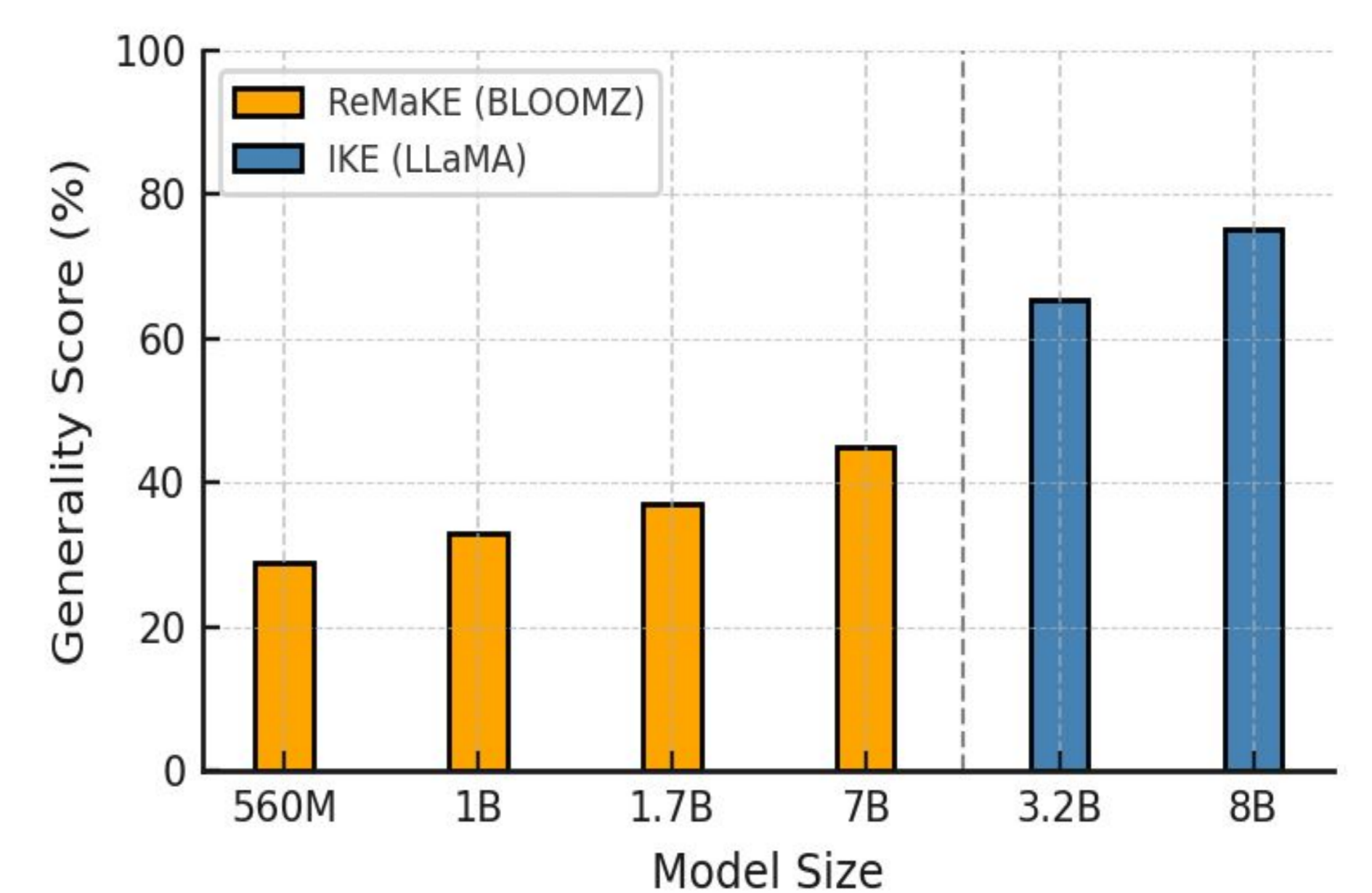
### Comparative Analysis

- **X-KDE** → best balance of reliability, generality, locality
- **Parameter editors & fine-tuning** → poor cross-lingual performance
- **Memory-based methods** → limited reliability & portability
- **Hypernetworks** → promising but underexplored



### Cross-lingual Analysis

- Edits transfer better **within related languages** or **shared scripts**
- High-resource languages transfer **more effectively** than low-resource ones
- **Multi-hop reasoning** further weakens cross-lingual transfer.



### Effect of Model Size

- **Larger** and more capable models consistently yield **higher editing quality**
- **Instruction tuning** further enhances **robustness**
- Stronger models **stabilize weak** editing methods

## Benchmarks

• MLaKE (Wei et al., 2025)	5	✓	• MQuAKE-AR (Ali et al., 2025)	1	✓
• MzSRE (Wang et al., 2024d)	12	🤖	• MQuAKE (Khandelwal et al., 2024)	7	✓
• biZsRE (Wang et al., 2024a)	2	⚠	• DocTer (Wu et al., 2023)	2	?
• BMIKE-53 (Nie et al., 2025)	53	⚠	• Counterfact (Tamayo et al., 2024)	2	✓
• MKEB (Xie et al., 2024)	12	🤖	• CKnowEdit (Fang et al., 2024)	1	✓

## Opportunities

Cultural Benchmarks  
 Multi-source Editing  
 Cross-Model Editing and Transfer  
 Language Conditioned Editing