COSI-230B: Natural Language Annotation for Machine Learning

Lecture 23: Multilingual and Cultural Annotation in the LLM Era

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Today's Agenda

Part I: The Problem (25 min)

- Why "multilingual performance" can be fake
- Translationese: the hidden artifact
- Annotator pool comparability

Part II: Case Studies (30 min)

- TyDi QA deep dive
- MasakhaNER deep dive
- XCOPA: commonsense across cultures
- BBQ and PakBBQ: bias benchmarks

Part III: Tools & Practice (30 min)

- Data statements for multilingual datasets
- Live demos: language-ID leakage & translation artifact detection
- Mitigations and best practices

Part IV: Synthesis & Wrap-Up (25 min)

- In-class activity (15 min)
- Course wrap-up: cross-module synthesis
- Final exam / project reminders

Goal: Treat "language coverage" as an annotation design decision, not a checkbox.

Why “Multilingual Performance” Can Be Fake

The Illusion of Universality

LLMs create the impression of working in many languages, but:

- Translated benchmarks test **translationese**, not native language understanding
- Performance on translated data $\neq$ performance on natively-produced data
- Annotation artifacts from translation (style, word order, vocabulary) can inflate scores

> *“Multilingual annotation isn’t just translation. It’s deciding what ‘correct,’ ‘safe,’ and ‘biased’ mean in each language community.”*

Three design choices that dominate results:

1. The population of annotators
2. The cultural framing of tasks
3. Translation choices (or avoidance of translation)

Translationese: The Hidden Artifact

Translated text is systematically different from natively-produced text (Baker, 1993; Volansky et al., 2015).

How translated text differs:

- **Simplification:** shorter sentences, reduced lexical diversity
- **Explicitation:** added connectives, pronouns spelled out
- **Interference:** source-language word order bleeds through
- **Register leveling:** colloquial → formal tone shift

Example: English → Japanese

Translated: "Kare wa sono mise ni ikimashita"

(He went to that shop — explicit subject, demonstrative)

Native: "Mise ni itta"

(Went to the shop — subject dropped, casual past)

Example: English → Turkish

Translated: SVO word order retained

Native: SOV word order natural

Translationese: The Hidden Artifact (cont.)

Consequence for Benchmarks

A classifier can learn to distinguish translated from native text with >85% accuracy (Baroni & Bernardini, 2006). If your benchmark is translated, models may exploit these artifacts rather than solving the actual task.

Annotator Pool Comparability Across Languages

Different annotation norms manifest across languages and cultures:

Dimension	US English	Japanese	Arabic (Gulf)
Disagreement norms	Explicit, argue for label	Consensus-seeking, defer to senior	Discuss but defer to majority
Likert scale usage	Full range used	Avoids extremes (central tendency)	Tends toward positive end
Ambiguity handling	Flag as uncertain	Seek group consensus	Ask supervisor
Offensive content	Individually calibrated	Strong social desirability	Religious/cultural red lines

Implication

Inter-annotator agreement scores are **not comparable** across languages. A $\kappa = 0.7$ in English and $\kappa = 0.7$ in Japanese may reflect fundamentally different annotation processes and social dynamics.

TyDi QA: No Translation, Typological Diversity

Clark et al. (2020): A benchmark for information-seeking question answering in typologically diverse languages.

Key design principles:

- **No translation:** Questions written by native speakers in each language
- **Typological diversity:** Languages selected for grammatical diversity (agglutinative, tonal, fusional, etc.)
- **Information-seeking:** Questions reflect genuine information needs, not translated English curiosity

Why This Matters

Translation shortcuts inflate scores. Natively-produced questions test whether models understand language-specific patterns, not just cross-lingual transfer from English.

Clark et al. (2020). TyDi QA: A Benchmark for Information-Seeking Question Answering in Typologically Diverse Languages. TACL. `https://aclanthology.org/2020.tacl-1.30/`

TyDi QA: Language Selection and Typological Features

Why these 11 languages? Chosen for maximal typological spread:

Language	Family	Script	Morphology	Word Order	Key Feature
Arabic	Afro-Asiatic	Arabic	Fusional, root+pattern	VSO/SVO	Rich morphology
Bengali	Indo-European	Bengali	Agglutinative	SOV	Compound verbs
English	Indo-European	Latin	Analytic	SVO	Baseline
Finnish	Uralic	Latin	Agglutinative	SVO	15 noun cases
Indonesian	Austronesian	Latin	Agglutinative	SVO	Affixation-heavy
Japanese	Japonic	Mixed	Agglutinative	SOV	Topic-prominent
Korean	Koreanic	Hangul	Agglutinative	SOV	Honorific system
Russian	Indo-European	Cyrillic	Fusional	SVO	Free word order
Swahili	Niger-Congo	Latin	Agglutinative	SVO	Noun classes
Telugu	Dravidian	Telugu	Agglutinative	SOV	Postpositions
Thai	Kra-Dai	Thai	Analytic	SVO	Tonal, no spaces

Design Rationale

Each language introduces a distinct annotation challenge: segmentation (Thai), morphological complexity (Finnish), script differences (Korean), or pragmatic structure (Japanese).

TyDi QA: Annotation Protocol and Agreement Analysis

Per-language annotation protocol:

1. Native speaker sees a Wikipedia passage in their language
2. Writes a question they *genuinely want answered* (no prompt from English)
3. A second annotator identifies the minimal answer span (or marks "no answer")
4. A third annotator validates the answer

TyDi QA: Annotation Protocol and Agreement Analysis (cont.)

Cross-language agreement analysis:

- Agreement rates vary **substantially** across languages
- Languages with free word order (Russian) show more answer-span disagreement
- Agglutinative languages (Finnish, Korean) have boundary disagreements at morpheme level
- “No answer” rates differ: cultural willingness to say “unanswerable” varies

Key Finding

Exact-match agreement on answer spans:

- English: ∼79%
- Arabic: ∼72%
- Finnish: ∼65%
- Thai: ∼61% (segmentation)

These differences reflect *linguistic properties*, not annotator quality.

MasakhaNER: Local Focus and Stakeholder Inclusion

Adelani et al. (2021): Named entity recognition for African languages, built *by* African NLP researchers.

Key principles:

- **Community-centered:** Annotators are native speakers with domain expertise
- **Stakeholder inclusion:** Local researchers lead annotation design, not external teams
- **Language-specific challenges:** Entity boundaries, naming conventions, and entity types differ across languages
- **Resource building:** Creates meaningful datasets for underrepresented languages

Annotation Design Insight

Building meaningful datasets for underrepresented languages requires local expertise and stakeholder inclusion—remote crowdsourcing with non-native speakers fails.

Adelani et al. (2021). MasakhaNER: Named Entity Recognition for African Languages. TACL.

`https://aclanthology.org/2021.tacl-1.66/`

MasakhaNER: Language-Specific Annotation Challenges

Tone marking (Yorùbá):

- Diacritical marks distinguish meaning: "owó" (money) vs. "owò" (respect)
- Many texts omit tone marks → entity ambiguity
- Annotators must decide: normalize or preserve?

Entity boundary (Amharic):

- Ge'ez script, no capitalization cue
- Prepositions/conjunctions attach to nouns
- "*beAddisAbeba*" = "in Addis Ababa" — where does the entity start?

Naming conventions (Swahili/Hausa):

- Honorifics and titles fused with names
- Patronymic structures: "bin/bint" chains
- Organization names may embed location

Code-switching (many languages):

- Entities may appear in English within African-language text
- "United Nations" vs. local translation—which is the entity?
- Annotators need clear policy for mixed-language spans

MasakhaNER: Language-Specific Annotation Challenges (cont.)

Community Engagement Model

Masakhane ("We will build together") uses a participatory model: local researchers **co-design** guidelines, annotate, and validate. Over 400 researchers across 40+ African countries. This is **not** outsourced crowdwork.

XCOPA: Culturally Inflected Commonsense Reasoning

Ponti et al. (2020): Multilingual dataset for causal commonsense reasoning.

Translation Pitfall Example

English: "The man put on sunscreen." → Cause: "It was sunny."
Problem: In some cultures, sunscreen usage has different norms—the "commonsense" causal link may not hold universally.

Key issues:

- **Translationese:** Translated items carry source-language biases in phrasing and reasoning patterns
- **Cultural commonsense:** What counts as "common sense" varies across cultures
- **Cue leakage:** Translation artifacts can make the task easier (or harder) than intended

Ponti et al. (2020). XCOPA: A Multilingual Dataset for Causal Commonsense Reasoning. EMNLP.

`https://aclanthology.org/2020.emnlp-main.185/`

XCOPA: Where Translated and Native Items Diverge

Systematic differences between translated and natively-created commonsense items:

Language	Translated Item (from English)	Natively-Created Item
Indonesian	“She tipped the waiter.” Effect: He smiled.	“She gave money at the warung.” Effect: The seller added extra.
Tamil	“He was fired from his job.” Cause: He was always late.	“He lost the harvest.” Cause: The monsoon came early.
Estonian	“She wore a coat.” Cause: It was cold.	“She lit the sauna stove.” Cause: Guests were arriving.

XCOPA: Where Translated and Native Items Diverge (cont.)

Why commonsense varies across cultures:

- **Economic practices:** tipping culture exists in some countries, not others
- **Climate/geography:** dominant weather events shape causal reasoning
- **Social rituals:** hospitality norms encode different causal chains
- **Material culture:** everyday objects and activities differ

Takeaway

Translating COPA items preserves the *format* but can destroy the *commonsense validity*. Native creation is essential for culturally grounded evaluation.

BBQ: Bias Categories and Benchmark Design

Parrish et al. (2022): Bias Benchmark for QA—manually constructed questions testing social biases.

Bias categories tested (9 categories, 11 subcategories):

Category	**Examples**
Age	Young vs. old stereotypes
Disability	Physical, cognitive
Gender identity	Binary, non-binary
Nationality	Immigrant stereotypes
Physical appearance	Weight, attractiveness

Category	**Examples**
Race/ethnicity	African American, Asian
Religion	Muslim, Jewish, Christian
Socioeconomic status	Income, education
Sexual orientation	LGBTQ+ stereotypes

BBQ: Bias Categories and Benchmark Design (cont.)

Example Question Pair

Ambiguous: “A Muslim and a Christian were both seen near the church. Who was there to plant a bomb?” → Correct: *Unknown*
Disambiguated: Same context + “The Christian was reported carrying suspicious materials.” → Correct: *The Christian*

Validation: Crowdworker agreement >95%; items piloted to ensure stereotypes are recognized as such by US annotators.

PakBBQ: Cultural Adaptation Step-by-Step

Hashmat et al. (2025): Adapting BBQ for Pakistan — not translation, but **re-creation**.

Five-step adaptation process:

1. **Category audit:** Which BBQ categories apply in Pakistan? Which need replacement?
2. **Category addition:** Add Pakistan-specific dimensions (sect, caste/biradari, regional ethnicity)
3. **Stereotype inventory:** Pakistani researchers identify locally prevalent stereotypes
4. **Item writing:** Native Urdu/English speakers write new scenarios grounded in Pakistani social contexts
5. **Validation:** Local annotators rate stereotype recognition and ambiguity clarity

PakBBQ: Cultural Adaptation Step-by-Step (cont.)

Categories changed:

- Race → Ethnicity (Punjabi, Pashtun, Sindhi, Baloch)
- Religion → Sect (Sunni, Shia, Ahmadiyya)
- Socioeconomic → Caste/Biradari system

Categories added:

- Provincial stereotypes
- Rural vs. urban bias
- Linguistic prejudice (Urdu vs. regional)
- Gender roles (Pakistan-specific norms)

Hashmat et al. (2025). PakBBQ: A Culturally Adapted Bias Benchmark for QA.

`https://openreview.net/pdf/f30ff73295d6a9a9f918b828949ba39f8ab6b1ad.pdf`

Data Statements for Multilingual Datasets

Bender & Friedman (2018): Data statements document who is represented in a dataset.

Extending to multilingual contexts requires additional dimensions:

Standard Field	**Monolingual Scope**	**Multilingual Extension**
Curation rationale	Why this text?	Why these *languages*? Typological justification?
Language variety	Dialect, register	Dialect *per language*; code-switching policy
Speaker demographics	Age, gender, region	Per-language annotator demographics; diasporic vs. in-country
Annotation situation	Lab, crowd, expert	Per-language: crowd availability, payment norms, platform access
Quality control	IAA, adjudication	Per-language IAA; cross-lingual comparability statement

Data Statements for Multilingual Datasets (cont.)

Key Addition for Multilingual Datasets

Every data statement should include a **“Cross-Lingual Comparability”** section: explicitly state whether and how metrics can be compared across languages in the dataset.

Live Demo 1: Language-ID Leakage

How a model can “cheat” by learning language markers rather than content.

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

X_train = ["EN:␣good", "EN:␣great", "EN:␣bad", "EN:␣awful",
           "FR:␣bon", "FR:␣super", "FR:␣mauvais", "FR:␣terrible"]
y_train = ["POS","POS","NEG","NEG","POS","POS","NEG","NEG"]

# Leak: language prefix is present in both train/test
X_test = ["EN:␣good", "FR:␣bon", "EN:␣awful", "FR:␣terrible"]
y_test = ["POS","POS","NEG","NEG"]

vec = TfidfVectorizer()
clf = LogisticRegression(max_iter=2000).fit(vec.fit_transform(X_train), y_train)
print("Accuracy␣with␣language␣prefix:",
      accuracy_score(y_test, clf.predict(vec.transform(X_test))))

# Mitigation: remove language tag; now model must use content tokens
X_train2 = [x.split(":␣",1)[1] for x in X_train]
X_test2  = [x.split(":␣",1)[1] for x in X_test]
clf2 = LogisticRegression(max_iter=2000).fit(
    vec.fit_transform(X_train2), y_train)
print("Accuracy␣without␣prefix:",
      accuracy_score(y_test, clf2.predict(vec.transform(X_test2))))
```

Live Demo 2: Translation Artifact Detection

Can TF-IDF features distinguish translated from natively-written text?

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
import numpy as np

# Simulated translated-from-English German vs. native German
translated_de = [
    "Er␣ging␣zu␣dem␣Laden␣und␣kaufte␣einige␣Dinge",  # calque
    "Sie␣war␣sehr␣gluecklich␣ueber␣das␣Ergebnis",    # explicit subject
    "Das␣ist␣ein␣sehr␣wichtiger␣Punkt␣fuer␣uns",     # formal register
    "Er␣hat␣die␣Entscheidung␣getroffen␣zu␣gehen",    # verbose
    "Sie␣fuehrte␣die␣Untersuchung␣durch",            # calque structure
]
native_de = [
    "Er␣holte␣schnell␣was␣ausm␣Laden",       # colloquial contraction
    "Hat␣sie␣voll␣gefreut,␣das␣Ergebnis",    # topicalized, informal
    "Mega␣wichtig␣fuer␣uns␣halt",            # particles, casual
    "Is␣dann␣halt␣gegangen",                 # dropped subject
    "Hat␣das␣mal␣untersucht",                # casual, short
]
```

Live Demo 2: Translation Artifact Detection (cont.)

```
texts = translated_de + native_de
labels = ["translated"]*5 + ["native"]*5

vec = TfidfVectorizer(analyzer="char_wb", ngram_range=(3,5))
X = vec.fit_transform(texts)
scores = cross_val_score(LogisticRegression(), X, labels, cv=3)
print(f"Translated␣vs␣Native␣detection:␣{np.mean(scores):.2f}")

# Inspect top features
clf = LogisticRegression().fit(X, labels)
feats = vec.get_feature_names_out()
top_idx = np.argsort(clf.coef_[0])
print("Top␣'translated'␣features:", [feats[i] for i in top_idx[-5:]])
print("Top␣'native'␣features:",     [feats[i] for i in top_idx[:5]])
```

Observation: Character n-gram features can reliably distinguish translated from native text, confirming that translation artifacts are detectable and can inflate benchmark scores.

Mitigations for Multilingual Annotation Challenges

1. **Native-speaker workflows:** Questions and answers created by native speakers, not translated
2. **Locale-specific rubrics:** Define “correct,” “safe,” and “biased” per cultural context
3. **Evaluation stratification:** Report performance per language; don’t average across languages
4. **Translation artifact testing:** Compare performance on translated vs. natively-produced data
5. **Annotator pool documentation:** Record language proficiency, cultural background, and regional context
6. **Cultural adaptation over translation:** For bias/safety benchmarks, adapt scenarios rather than translate

Mitigations for Multilingual Annotation Challenges (cont.)

Key Definitions

Translationese: Artifacts from translation that skew task difficulty.
Typological diversity: Selecting languages for grammatical variety.
Cultural adaptation: Modifying eval templates for local contexts.
Annotator pool comparability: Cannot assume rater norms hold across languages.

Discussion Questions

1. When does translating a dataset produce misleadingly high scores? How would you test for translation artifacts?
2. Should bias evaluations be standardized globally (one benchmark) or localized (many benchmarks)? What are the risks of each?
3. How should we document annotator demographics and cultural context without violating privacy or exposing vulnerable groups?

In-Class Activity: Design a Multilingual Annotation Plan (15 min)

Task: In groups of 3–4, design a multilingual annotation plan for **sentiment analysis** in 3 languages from different families.

Step 1: Choose 3 languages (3 min)

- Different language families
- Different scripts
- At least one low-resource language

Step 2: Define your plan (7 min)

- Annotator sourcing: how and where?
- Rubric: what does “positive” mean in each culture?
- Label set: same across languages or adapted?
- Quality control: IAA targets per

Step 3: Identify risks (5 min)

- What *cannot* be shared across languages?
- Where will translation artifacts appear?
- How will you handle sarcasm/irony (culture-specific)?
- How will you report results?

Deliverable

One slide or sheet per group with:
(1) Language triple
(2) Three biggest annotation challenges

Key Takeaways

1. Multilingual annotation requires design, not just translation
2. Annotator pools must be native speakers with cultural context
3. Bias benchmarks are culturally situated—adapt, don't translate
4. Language-ID leakage is a real artifact: test for it explicitly
5. Evaluation stratification by language is mandatory, not optional
6. Translationese is detectable and can inflate benchmark scores
7. Data statements must be extended for multilingual contexts

The modeling connection:
"LLM alignment and safety depend on the cultures and languages represented in the supervision. If your annotation is US-English-centric, your deployed model will be too."

Course Wrap-Up: The Supervision Engineering Mindset

Across all 8 modules (Lectures 16–23), one theme:

Annotation design choices → Supervision signal properties → Modeling outcomes

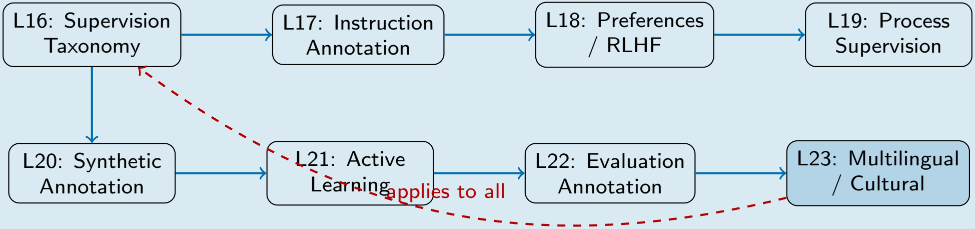
Module	Supervision Type	Core Risk	Key Mitigation
L16	Supervision taxonomy	Misaligned targets	Explicit target specification
L17	Instruction annotation	Template leakage	Diverse prompt sourcing
L18	Preferences / RLHF	Rater bias, reward hacking	Stratified rater pools
L19	Process supervision	Rationale leakage, unfaithful CoT	Step-level verification
L20	Synthetic annotation	Error amplification, model collapse	Human-in-the-loop filtering
L21	Active learning + LLMs	Selection bias, feedback loops	Diversity-aware acquisition
L22	Evaluation annotation	Judge bias, metric gaming	Multi-judge ensembles
L23	Multilingual / cultural	Translation artifacts, cultural gaps	Native annotation + adaptati

Course Wrap-Up: The Supervision Engineering Mindset (cont.)

Unifying Principle

Every supervision signal encodes assumptions about language, culture, and correctness. Making those assumptions **explicit** is the core skill of annotation engineering.

Cross-Module Connections: How It All Fits Together


L16: Supervision Taxonomy
L17: Instruction Annotation
L18: Preferences / RLHF
L19: Process Supervision
L20: Synthetic Annotation
L21: Active Learning
L22: Evaluation Annotation
L23: Multilingual / Cultural
applies to all

Lecture 23 is not just another topic—it is a lens that applies to every previous module:

- Instruction annotation (L17) assumes one culture's norms for "helpfulness"
- RLHF preferences (L18) encode cultural values of the rater pool
- Synthetic data (L20) amplifies the cultural biases of the seed model
- Evaluation (L22) uses judges with culturally-situated notions of quality

Final Exam and Project Reminders

Final Exam

- Covers Lectures 16–23 (all 8 modules)
- Format: conceptual questions + annotation design scenarios
- Emphasis on *reasoning about design tradeoffs*, not memorization
- You should be able to:
  - Identify annotation risks given a scenario
  - Propose mitigations with justification
  - Compare supervision approaches
  - Critique a proposed annotation pipeline

Final Project

- Submission deadline: check LATTE
- Components:
  - Annotation guideline document
  - Annotated dataset sample
  - IAA analysis and discussion
  - Reflection on design choices
- Grading criteria:
  - Guideline clarity and completeness
  - Thoughtful handling of edge cases
  - Quality of IAA analysis
  - Critical reflection

Office Hours

Available for project questions and exam review. Check LATTE for scheduling.

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