# Diversity quantification in natural language processing: The why, what, where and how

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UniDive
cost EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY
Funded by the European Union

# Welcome!

We are very happy to welcome this large and very diverse group of trainees to our course.

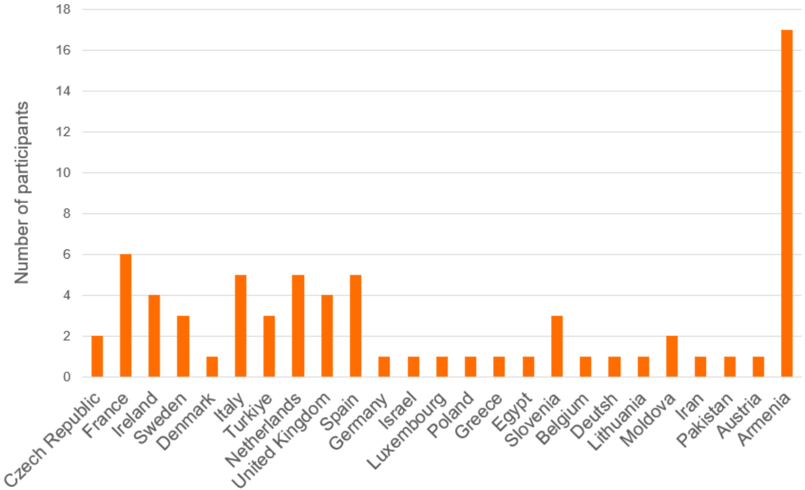
# But . . . what do we actually mean by a **diverse group**?

# But ... what do we actually mean by a **diverse group**?

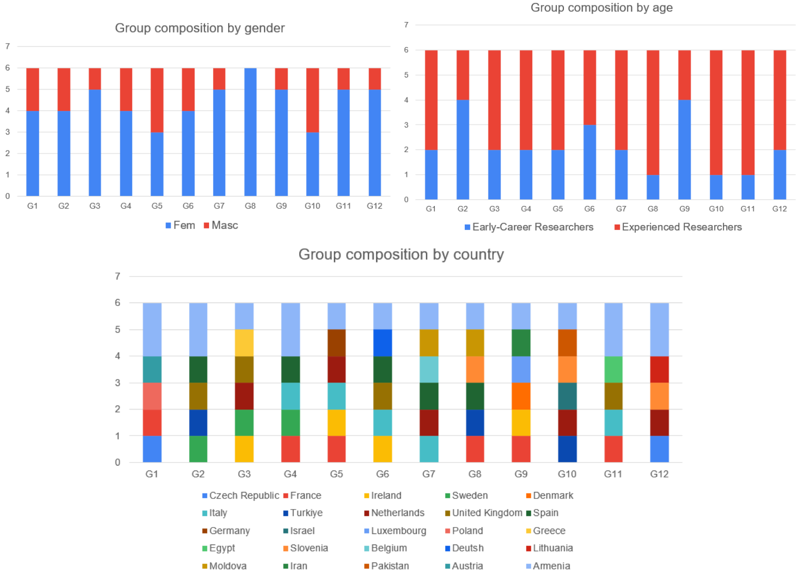
## Intuitions

- From how many countries?
- How many from ITC vs. non-ITC countries?
- How many female vs. male vs. prefer-not-to-say?
- How many young researchers vs. senior researchers?
- How many different backgrounds?
- Speaking how many mother tongues?
- How different are these mother tongues?

# But . . . what do we actually mean by a **diverse group**?



# Are some trainee groups more diverse than the others?



# Objectives of the course

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- Understanding the **challenges** behind various approaches to diversity in NLP,
- Transition from intuitive diversity assumptions to **rigorous** quantitative assessment,
- Promoting a **unified framework**, inspired by other scientific fields (e.g. ecology), for modeling **diversity quantification** in NLP

## Learning outcomes

- **Theoretical** understanding of diversity quantification in NLP
- **Practical** skills in quantifying diversity in NLP datasets

# Course schedule

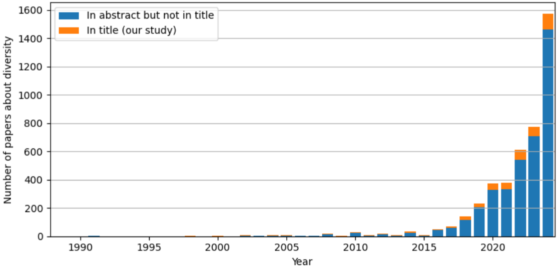
| | Monday 19 January | Tuesday 20 January | Wednesday 21 January | Thursday 22 January | Friday 23 January | Saturday 24 January | Sunday 25 January |
|---|---|---|---|---|---|---|---|
| 8:30-9:00 | UniDive WG4 meeting | Registration, poster hanging | | | | | |
| 9:00-9:15 | | (session 1) Opening session | (session 7) **LLMs for Low-Resourced Languages** (Nina Hosseini & Dimitra Anastasiou) Foundations of LLMs + hands-on exercises | (session 10) Course 1: **Linguistic typology for NLP** (Harald Hammarström & Luigi Talamo) Hands-on working with language diversity resources | (session 13) **LLMs for Low-Resourced Languages** (Nina Hosseini & Dimitra Anastasiou) Fine-tuning in LLMs + hands-on exercises | (session 16) Course 1: **Linguistic typology for NLP** (Harald Hammarström & Luigi Talamo) Linguistic diversity and NLP | journey |
| 9:15-9:45 | | (session 2) Personal introductions | | | | | |
| 9:45-11:00 | | (session 3) Poster session | | | | | |
| 11:00-11:30 | | coffee break | coffee break | coffee break | coffee break | coffee break | |
| 11:30-13:00 | | (session 4) Poster session | (session 8) Course 3: **Diversity quantification** (Louis Estève et al.) Measuring in-text diversity (practical session) | (session 11) Course 3: **Diversity quantification** (Louis Estève et al.) Measuring metalinguistic diversity (practical session) | (session 14) Course 3: **Diversity quantification** (Louis Estève et al.) Trainees' presentations of the outcomes from sessions 2 and 4 | (session 17) **Brainstorming** hackaton (on open issues submitted by the trainees) | |
| 13:00-14:30 | | lunch | lunch | lunch | lunch | lunch | |
| 14:30-16:00 | | (session 5) Course 3: **Diversity quantification** (Louis Estève et al.) Diversity quantification taxonomy | (session 9) Course 1: **Linguistic typology for NLP** (Harald Hammarström & Luigi Talamo) Languages of the world | (session 12) **LLMs for Low-Resourced Languages** (Nina Hosseini & Dimitra Anastasiou) Pretrained models and prompt engineering + hands-on exercises | (session 15) Course 1: **Linguistic typology for NLP** (Harald Hammarström & Luigi Talamo) Linguistic analysis | (session 18) **LLMs for Low-Resourced Languages** (Nina Hosseini & Dimitra Anastasiou) Bias, ethics, and evaluation + hans-on exercises | |
| 16:00-16:30 | | coffee break | | | | | |
| 16:30-17:00 | | (session 6) Course 3: **Diversity quantification** (Louis Estève et al.) Taxonomy in practice | coffee break | coffee break | coffee break | (session 19) Closing session | |
| 17:00-18:00 | | | | | | | |

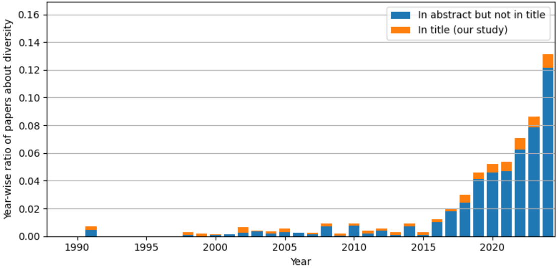
- Prerequisites
  - Reading a paper assigned to your group
- Sessions
  - Session 1 (Tuesday): This lecture
  - Session 2 (Tuesday): Group assignment – casting the assigned paper on the unified framework taught in the lecture
  - Session 3 (Wednesday): Practical session – Measuring in-text diversity
  - Session 4 (Thursday): Practical session – Measuring metalinguistic diversity
  - Session 5 (Friday): Trainees' presentations of the outcomes from Session 2

# A survey of diversity quantification in natural language processing: The why, what, where and how

- UniDive CA21167 COST action: Universality, Diversity and Idiosyncrasy in Language Technology
- Over 400 members from over 40 countries
- Working Group 4: Quantifying and promoting diversity
- International collaboration:
  - Louis Estève, LISN, Université Paris-Saclay, France
  - Marie-Catherine de Marneffe, Université Catholique de Louven, Belgium
  - Nurit Melnik, The Open University, Israel
  - Agata Savary, LISN, Université Paris-Saclay, France
  - Olha Kanishcheva, Heidelberg University, Germany, SET University, Kiev, Ukraine
- TACL submission (under review)

# Diversity: prevalence in NLP




Papers in the ACL Anthology from 1990–2024 with “diversity” or “diverse” in their title or abstract

# Diversity in NLP – first findings

## Corpus

- 308 papers ACL Anthology from 1990 to 2024-07-26 with *diversity*/*diverse* in their title

## Observations

- **Ubiquity** and the dramatically growing interest in diversity since 2016
- **Increasing diversity** is important in NLP but the **reasons** are **not explicit**
- Frequent use of *diversity* or *diverse* in a common sense, **without quantification**
- Cross-paper **inconsistencies** in diversity quantification:
    - 150 different measures
    - many ad hoc or unclear
    - no uniform terminology and methodology
- Choices of diversity **measures rarely justified**
- Limited attempts to systematize the notion of diversity [Tevet and Berant(2021), Ploeger *et al.*(2024)]

## Big picture

NLP belongs to the "fields [. . . ] where diversity is prominent in discussion, but remains undefined or analytically neglected" [Stirling(2007)]

# Objectives

- NLP-specific **framework** for **quantification** of diversity ⇒ Core of this course
  - **why** diversity is important in NLP
  - **what** objects are measured for diversity
  - **where** diversity is measured (ML pipeline stages)
  - **how** it is measured
- Positioning the papers along this taxonomy ⇒ Group work for the trainees

# Diversity in other scientific fields

## Ecology - diversity is a mature topic

- Dozens of diversity **measures** defined [Smith and Wilson(1996)] and applied to various species and their habitats
- Measures borrowed from **information theory**: parameterized entropies [Patil and Taillie(1982)] and related transformations [Hill(1973)].
- **Distance** measures (underlying diversity) based on functional differences (body features, behavior, etc.) and positions in the phylogenetic tree [Mouchet *et al.*(2010)].
- **Unified frameworks** [Leinster and Cobbold(2012), Scheiner(2012), Chao *et al.*(2014)].
- Debates on **properties** of diversity measures [Smith and Wilson(1996), Hoffmann and Hoffmann(2008), Jost(2009)].

## Unified framework across disciplines [Stirling(2007)]

- Element/category dichotomy
  - **Elements** (e.g. individuals) are apportioned into **categories** (e.g. species)
- Dimensions of diversity
  - **Variety** – related to the number of categories
  - **Balance** – evenness of the distribution of elements in categories
  - **Disparity** – extent of the differences between categories

# *Why* diversity is important in NLP: Ethics

- **equality and inclusiveness**
  - equally serving all users [Khanuja *et al.*(2023), Liu *et al.*(2024a)]
  - digital inclusiveness [Joshi *et al.*(2020)]
  - representing different languages, language families and scripts [Kodner *et al.*(2022), Goldman *et al.*(2023)]
  - mitigating the supremacy of English and English-centric bias [Pouran Ben Veyseh *et al.*(2022), Asai *et al.*(2022)]
  - fair account for diverse cultures [Yin *et al.*(2021), Mohamed *et al.*(2022), Keleg and Magdy(2023), Bhatia and Shwartz(2023), Liu *et al.*(2024a)], human perspectives [Parrish *et al.*(2024)] and opinions [Zhang *et al.*(2024)]
- **protection of users**
  - diverse attention vectors ⇒ low sensitivity to adversarial attacks [Yang *et al.*(2024)]
  - diverse prompt-response pairs ⇒ less offensive LLM answers [Song *et al.*(2024)]

# *Why* diversity is important in NLP: Ethical reasons

- **educational quality**
  - cover a large variety of **topics** in education [Hadifar *et al.*(2023)]
- **methodological rigor**
  - diverse benchmark ⇒ reliable evaluation [Chen *et al.*(2023b)]
  - showing out-of-domain performance [Pradhan *et al.*(2022)].
  - highlighting the remaining challenges [Kim *et al.*(2023c)]
  - dataset's diversity more critical in evaluation than its size [Miao *et al.*(2020)]

# *Why* diversity is important in NLP: Practical reasons

- **meeting user expectations**
  - diverse generated text ⇒ less generic and more informative [Park *et al.*(2023)]
  - diversity is inherent to human language ⇒ also expected in machine-generated language
  - need for **one-to-many** scenarios: diverse spectrum of outputs rather than a single most optimal output [Kumar *et al.*(2019), Liu *et al.*(2020), Han *et al.*(2021), Shao *et al.*(2022), Puranik *et al.*(2023), E *et al.*(2023), Hwang *et al.*(2023)]
  - high diversity expectations in **dialog** [Lee *et al.*(2022)]: diverse system's reactions ⇒ higher user's engagement [Akasaki and Kaji(2019), Kim *et al.*(2023b)]
  - naturalness: diversity of human language ⇒ upper bound for systems [Schüz *et al.*(2021), Cegin *et al.*(2023), Liu *et al.*(2024b)]
- **improving performance**
  - diverse training data ⇒ higher performance [Narayan and Cohen(2015), Liu and Zeldes(2023), Yang *et al.*(2018), Yadav *et al.*(2024), Tripodi *et al.*(2021), Shen *et al.*(2022), Li *et al.*(2016), Agirre *et al.*(2016), Zhu *et al.*(2018), Zhang *et al.*(2021), Thompson and Post(2020), Palumbo *et al.*(2020), Li *et al.*(2021)]
  - ensemble model with diverse submodels ⇒ better performances than a unique model [Song *et al.*(2021), Kobayashi *et al.*(2022)]
  - diverse keywords in class labels ⇒ more accurate classification [Yano *et al.*(2024)].

# *What* diversity is measured on

## In-text diversity

- Categories are inherent to a text: unique words, unique n-grams, sentences, syntactic trees
- Elements: word occurrences, n-gram occurrences, sentences, occurrences of syntactic trees

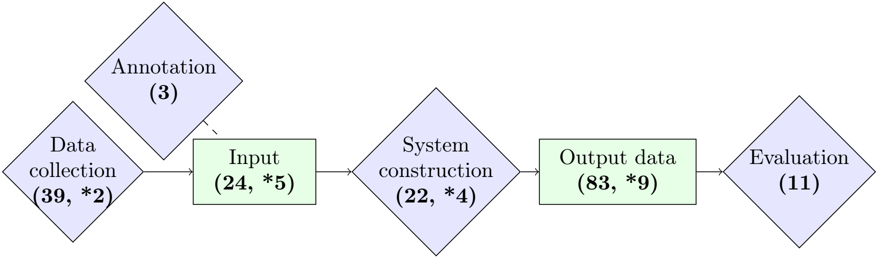
## Meta-linguistic diversity

- Categories are metadata of text: language, language family, branch in a phylogenetic tree, genre, domain, time period, racial identity or political opinion of the text author
- Elements: texts, language

## Diversity of processing

- Categories = elements: annotators, models (in an ensemble), NLP tasks, evaluation metrics, attention vectors
- diverse = several different

# *Where* diversity is measured



# *How* diversity is measured

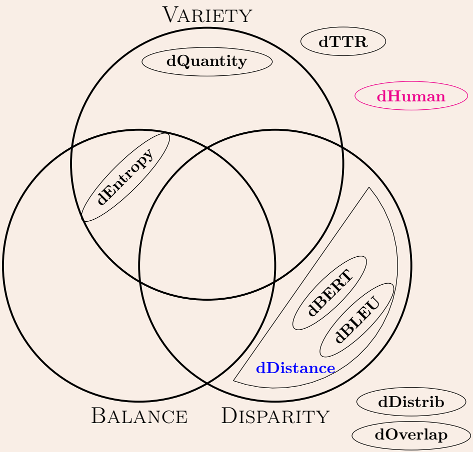
- 197 papers with actual quantification of diversity
- 150 different diversity measures ⇒ we group them into **3 approaches** and **9 families**
- 3 types of approaches:
  - **Absolute** quantification: a diversity score for the observed set independently of other sets
  - **Relative** quantification: a diversity of the observed set by comparison to a reference set
  - **Introspective** quantification: rank or score on a scale, by human judgment

# *How* diversity is measured

| Family of diversity measures | # |
|---|---|
| **dQuantity**: count categories | 55 |
| **dBLEU**: use BLEU for distances | 41 |
| **dDistance**: quantify differences between categories | 37 + 8 + 41 |
| **dTTR**: use the number of categories and normalize it by the number of elements | 30 |
| **dEntropy**: calculate unpredictability of categories | 21 |
| **dOverlap**: find the overlap between the categories in the observed set and in a reference set | 9 |
| **dBERT**: use BERT's contextual vector space for distances | 8 |
| **dHuman**: rely on a human evaluation | 7 |
| **dDistrib**: use the distance between observed and reference distributions | 3 |
| **dOther**: other measures | 36 |

# *How* diversity is measured

## Diversity measures in NLP cast on the 3 dimensions



# Absolute quantification

## Absolute quantification

Assigning a diversity score to the **observed set** independently of other sets.

## Parameters

- $n$ – number of (observed) categories
- $m$ – number of (observed) elements
- $P = \langle p_1, ..., p_n \rangle$ – distribution of categories,
- $D = \langle \langle d_{1,1}, ..., d_{1,n} \rangle, ..., \langle d_{n,1}, ..., d_{n,n} \rangle \rangle$ – pairwise distances between the categories.

# Absolute quantification

**dQuantity $\in$ Variety**

Variants of:

$$\texttt{richness}\,(n, m, P, D) = n \tag{1}$$

e.g. number of languages, language families, genres etc. in a dataset (meta-linguistic diversity).

**dTTR $\notin$ {Variety, Balance, Disparity}**

Variants of:

$$\texttt{type-token-ratio}\,(n, m, P, D) = \frac{n}{m} \tag{2}$$

Frequently: `Distinct-n`, `Dist-n` or `Diverse-n`:

- ratio of **distinct n-grams** to the total number of tokens [Li *et al.*(2016)], $n \in [1, 4]$
- issues: not monotonic to $n$

# Absolute quantification

## dEntropy $\in$ {Variety, Balance}

Mostly [Shannon and Weaver(1949)]:

$$\texttt{entropy}\,(n, m, P, D) = \sum_{i=1}^{n} p_i \log_b \left(p_i^{-1}\right) \tag{3}$$

Monotonic with $n$. Maximum value $log_b(n)$ with uniform distribution.

## dDistance $\in$ {Disparity}

- Aggregation and normalization of pairwise distances between categories [Kim *et al.*(2024)], complexity $O\left(n^2\right)$:

$$\texttt{pairwise}\,(n, m, P, D) = \frac{2 * \sum_{i=1}^{n} \sum_{j=1}^{i-1} d_{i,j}}{n(n-1)} \tag{4}$$

- Volume of the geometry formed by vector vertices, e.g. convex hall [Yang *et al.*(2024)]
- Entropy of distances [Yu *et al.*(2022)]

# Absolute quantification

## dBLEU $\in$ dDistance $\in$ {Disparity}

Mostly average of BLEU between two texts [Zhu *et al.*(2018)], variant of `pairwise`:

$$\text{Self-BLEU}\left(n, m, P, D\right) = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \text{BLEU}\left(\text{sent}_i, \text{sent}_j\right)}{n^2} \tag{5}$$

The lower Self-BLEU, the larger the diversity.

## dBERT $\in$ dDistance $\in$ {Disparity}

Mostly BERT score [Zhang* *et al.*(2020)]: F-measure between two texts $X$ and $Y$:

$$R_{\text{BERT}} = \frac{1}{|X|} \sum_{x_i \in X} \max_{y_j \in Y} \vec{x_i}^{\top} \vec{y_j} \tag{6}$$

$$P_{\text{BERT}} = \frac{1}{|Y|} \sum_{y_j \in Y} \max_{x_i \in X} \vec{y_j}^{\top} \vec{x_i} \tag{7}$$

$$F_{\text{BERT}} = 2 \frac{P_{\text{BERT}} \cdot R_{\text{BERT}}}{P_{\text{BERT}} + R_{\text{BERT}}} \tag{8}$$

# Relative quantification

## Relative quantification

Assigning a diversity score to the **observed set** $O$ in comparison to a **reference set** $R$. Two opposed variants:

- $R$ is considered diverse, e.g. it is curated with diversity in mind, and $O$ should be as close as possible to $R$ [Samardzic *et al.*(2024)]
- $O$ is expected to differ from $R$, e.g. generated utterances should be different from the training utterances [Murahari *et al.*(2019)]

## dDistrib $\notin$ {Variety, Balance, Disparity}

Distributions $P$, $Q$ of categories in $R$ and $O$ are compared, e.g.:

$$\texttt{cross-entropy}\left(Q, P\right) = \sum_{i=1}^{n} q_i \log_b \left(p_i^{-1}\right) \quad (9)$$

## dOverlap $\notin$ {Variety, Balance, Disparity}

Categories in $R$ and $O$ are compared, e.g.:

$$\texttt{Jaccard}\left(n_R, n_O\right) = \frac{|n_R \cap n_O|}{|n_R \cup n_O|} \quad (10)$$

# Introspective quantification

**dHuman $\notin$ {Variety, Balance, Disparity}**

Humans are asked to judge diversity by:

- ranking text samples for diversity [Liu *et al.*(2023)]
- scoring text samples along a diversity scale [Kim *et al.*(2023a)]

We cannot a priori know if humans rely on categories and elements for their judgment.

# Prototypical scenarios

### Scenario 1: Corpus creation

- Where: *data collection*
- Why: ensuring inclusiveness and equality (*ethical reason*) and/or ensuring performance (*practical reason*)
- What: *meta-linguistic* categories – text genres, languages, language genera, language families
- How: measures from *dQuantity* (variety)
- Example: highly multilingual morphological inflection [Vylomova *et al.*(2020)]

### Scenario 2: Generation

- Where: *output data*
- Why: user expectation or naturalness (*practical reason*), e.g. enhance chatbot responses for diversity and relevance simultaneously *one-to-many* scenario
- What: *in-text* categories – n-grams, sentences, etc.
- How: measures from *dTTR* or *dDistance*
- Example: enhance chatbot responses for diversity and relevance, by a summarizing latent variable inside an RNN [Liu *et al.*(2023)]

# Vylomova et al. (2020) *SIGMORPHON 2020 shared task: Typologically diverse morphological inflection*

*A broad goal in natural language processing (NLP) is to develop a system that has the capacity to process any natural language. Most systems, however, are developed using data from just one language such as English. The SIGMORPHON 2020 shared task on morphological reinflection aims to investigate systems' ability to generalize across typologically distinct languages, many of which are low resource. Systems were developed using data from 45 languages and just 5 language families, fine-tuned with data from an additional 45 languages and 10 language families (13 in total), and evaluated on all 90 languages. A total of 22 systems (19 neural) from 10 teams were submitted to the task. All four winning systems were neural (two monolingual transformers and two massively multilingual RNNbased models with gated attention). Most teams demonstrate utility of data hallucination and augmentation, ensembles, and multilingual training for low-resource languages. Nonneural learners and manually designed grammars showed competitive and even superior performance on some languages (such as Ingrian, Tajik, Tagalog, Zarma, Lingala), especially with very limited data. Some language families (Afro-Asiatic, Niger-Congo, Turkic) were relatively easy for most systems and achieved over 90% mean accuracy while others were more challenging.*

# Vylomova et al. (2020)

## What is the paper about?

A shared task on morphological inflection. Task: generate inflected forms from a lemma and a set of features.

## Why is diversity important?

- *English is just one morphological system among many. A larger goal of natural language processing is that the system work for any presented language.*
    - Ethical reasons: equality, inclusiveness, mitigating supremacy of English
- *Investigate systems' ability to generalize across typologically distinct languages, many of which are low-resource*
    - Practical reason: system's performance

# Vylomova et al. (2020)

## Quantification 1

*Data in 90 languages*

- What objects are measured for diversity
  - Elements: `(lemma, form, features)` triples
  - Categories: languages
  - Meta-linguistic diversity
- Where diversity is measured
  - Pipeline stage: Data collection
- How diversity is measured
  - Richness $\in$ dQuantity $\in$ Variety
  - Absolute quantification

# Vylomova et al. (2020)

## Quantification 2

*90 languages from 34 language genera*

- What objects are measured for diversity
  - Elements:

# Vylomova et al. (2020)

## Quantification 2

*90 languages from 34 language genera*

- What objects are measured for diversity
  - Elements: languages
  - Categories:

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## Quantification 2

*90 languages from 34 language genera*

- What objects are measured for diversity
  - Elements: languages
  - Categories: language genera
  - Meta-linguistic diversity
- Where diversity is measured
  - Pipeline stage:

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## Quantification 2

*90 languages from 34 language genera*

- What objects are measured for diversity
  - Elements: languages
  - Categories: language genera
  - Meta-linguistic diversity
- Where diversity is measured
  - Pipeline stage: Data collection
- How diversity is measured

# Vylomova et al. (2020)

## Quantification 2

*90 languages from 34 language genera*

- What objects are measured for diversity
  - Elements: languages
  - Categories: language genera
  - Meta-linguistic diversity
- Where diversity is measured
  - Pipeline stage: Data collection
- How diversity is measured
  - Richness $\in$ dQuantity $\in$ Variety
  - Absolute quantification

# Vylomova et al. (2020)

## Quantification 3

*34 language genera from 15 language families*

- What objects are measured for diversity
  - Elements:

# Vylomova et al. (2020)

## Quantification 3

*34 language genera from 15 language families*

- What objects are measured for diversity
    - Elements: language genera
    - Categories:

# Vylomova et al. (2020)

## Quantification 3

*34 language genera from 15 language families*

- What objects are measured for diversity
    - Elements: language genera
    - Categories: language families
    - Meta-linguistic diversity
- Where diversity is measured
    - Pipeline stage:

# Vylomova et al. (2020)

## Quantification 3

*34 language genera from 15 language families*

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# Vylomova et al. (2020)

### Quantification 3

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- How diversity is measured
    - Richness $\in$ dQuantity $\in$ Variety
    - Absolute quantification

# Liu et al. (2023) *PVGRU: Generating Diverse and Relevant Dialogue Responses via Pseudo-Variational Mechanism* [Liu *et al.*(2023)]

**What is the paper about?**

Response generation for multiturn dialogue in generative chatbots.

**Why is diversity important?**

*There is no simple one-to-one mapping between dialogue context and response. This variability in dialogue should be reflected in dialogue systems.*

- Practical reason: users' expectations

# Liu et al. (2023)

## Quantification 1

Number of distinct uni-grams/bi-grams divided by the total amount of generated words, in a response generated by the system.

- What objects are measured for diversity
    - Elements:

# Liu et al. (2023)

## Quantification 1

Number of distinct uni-grams/bi-grams divided by the total amount of generated words, in a response generated by the system.

- What objects are measured for diversity
  - Elements: unigram and bigram occurrences
  - Categories: distinct unigrams and bigrams
  - In-text diversity
- Where diversity is measured
  - Pipeline stage: Output data
- How diversity is measured
  - Dist-1/2 $\in$ dTTR
  - Absolute quantification

# Liu et al. (2023)

## Quantification 2

100 randomly sampled input contexts and system responses are read by human experts. The system response is evaluated, on a scale for how far it is informative (rather than generic and containing repeated information).

- What objects are measured for diversity
    - Elements:

# Liu et al. (2023)

## Quantification 2

100 randomly sampled input contexts and system responses are read by human experts. The system response is evaluated, on a scale for how far it is informative (rather than generic and containing repeated information).

- What objects are measured for diversity
  - Elements: system responses (utterances)
  - Categories: same as elements
  - In-text diversity
- Where diversity is measured
  - Pipeline stage: Output data
- How diversity is measured
  - Scale $\in$ dHuman
  - Introspective quantification

# Group assignment for session 2

- Analyse you pre-requisite papers within this framework
- Prepare slides based on the ▸ template
- Elect a group representative who will present the slides on **Friday** (**5-minute** presentation + 2-minute discussion)

# Bibliography I


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# Discreteness vs. continuousness

- 28% papers: diversity measures (dBLEU, dBERT) applied directly to elements
  - trivial disparity: elements = categories
  - variety = dataset size
  - balance is moot
- tension:
  - NLP – continuous representations
  - ecology – categorical modelling
  - reason for little popularity of the diversity theory in NLP ?

# Diversity vs. naturalness

## Correlation

- Scenario 1
  - Natural phenomenon: few languages are well-resourced and many others are not
  - Compensation by diversity-driven data selection
  - Diversity and naturalness are **opposed**
- Scenario 2
  - Diversity of human answers = upper bound for the systems' generations
  - Diversity and naturalness are **positively correlated**

## Naturalness of categories

- (Meta-)linguistically meaningful (natural) categories: words, idiomatic expressions, sentences, syntactic trees, genres, language families, typological features, speakers, countries, ethnicities, NLP tasks, etc.
- Non-linguistic (artificial) categories: n-grams, BERT word pieces, word embeddings, attention vectors, points in a vector space, etc. (approximations of natural categories whose diversity might be too hard to compute)

# Tendencies in diversity endorsement

## Quest for diversity

- Most works advocate for an **increase of diversity**
- Few posit adjustment to the task: factual ⇒ low diversity, storytelling ⇒ high diversity
- Few see lower diversity of AI vs. human language as opportunity: bot detection, fack checking, protection of democracy

## Quality/diversity trade-off

- Opposing objectives: quest for diversity vs. generative quality and consistence [Ma *et al.*(2024), Ippolito *et al.*(2019), Zhang *et al.*(2021), Shao *et al.*(2022), Chen *et al.*(2023a)]

## Interest in theorizing diversity

- better understanding of the nature of **typological** diversity [Ploeger *et al.*(2024)]
- making **educated choices** of diversity measures [Tevet and Berant(2021), Lion-Bouton *et al.*(2022)]
- **comparative framework** in typological diversity for NLP [Poelman *et al.*(2024)]
- Our work