Stylometry and the interplay of title and L1 in the different annotation layers in the Falko corpus

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QITL 4 – 31.03.2011
Research Questions: Joining two points of view

2 Background SLA
   - Interlanguage
   - Transfer

3 Learner Corpus Research on transfer

4 Current study
   - Road map
   - Our data - the Falko corpus

5 The similarity measure $S$ – basic concept

6 Classification according L1
   - Preliminary results
   - Taking the essay *title* into account
   - Getting rid of copied material
   - Summarizing classification (stylometric) results

7 Beyond stylometry, beyond classification

8 Conclusion
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Coming from second language acquisition research

Learner Corpus Research

1. study of learner language
   ▶ patterns
   ▶ development
   ▶ controlling variables
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2. and describe the variability between learners and learner subgroups
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   - patterns
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2. and describe the variability between learners and learner subgroups

What measures can help us uncover hidden patterns in learner data?

1. Are learner dependent variables detectable in learner texts?
2. How do those variables affect the learner language?
3. How strong is the influence of those variables?
Coming from stylometry

Stylometry...
Coming from stylometry

Stylometry...  

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Coming from stylometry

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   - authorship (who wrote a piece?)
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   - gender
   - other such variables.

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Can we apply this technique to learner data?

1. Can we automatically “detect” the learners L1 from her texts?
2. What kind of variables play a (confounding) role?
3. Can we isolate the influence of different variables?
Converging research questions

1. Can we quantify the influence of the learner’s L1 on his/her language use?
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2. How do L1 effects show on different linguistic levels?
   - lexis
   - syntax
   - morphology
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2. How do L1 effects show on different linguistic levels?
   - lexis
   - syntax
   - morphology

3. To what extent do L1-effects lead to ungrammatical structures in the learner language?
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Studying language learners as a group, we assume that
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1 learners of a second/foreign language have a systematic internal grammar (interlanguage: IL)
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4. IL has been claimed to be influenced by

▶ general learning principles (developmental factors)
▶ the structure of the target language
▶ the learner's L1 (transfer)
▶ mode of acquisition, teaching method, learning strategies, psychological aspects, etc.
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Transfer as cross-linguistic influence

- Large discussion about what transfer is
  (Gass et al. 1983; Dechert et al. 1989; Ellis 2009)

- processing mechanism
- learning strategy
- performance/competence phenomenon

- constrains on hypothesis building
- structural borrowing
- etc.
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Working definition

Language transfer refers to any instance of learner data where a statistically significant correlation (or probability-based relation) is shown to exist between some feature of the interlanguage and any other language that has been previously acquired (see Ellis 2009)
Transfer on different linguistic levels

- Transfer operates on various linguistics levels.

Many studies have looked at each level independently:
- phonology (Broselow 1992)
- morphology (e.g. Duskova 1984; Jarvis 2000)
- syntax (e.g. Odlin 1990)
- semantics (e.g. Kellermann 1979)
- lexicon (e.g. Ringbom 1992)
- conceptualization (e.g. Stutterheim 1999, Slabova 2000)
- etc.

We need a reliable way to measure the relative contributions of the native language to the ease or difficulty learners have with each subsystem and, by implication, the total contribution of transfer to the process of second language acquisition. (Odlin 2003, p. 439)
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Transfer as overuse/underuse

- Some studies have studied transfer by comparing frequencies of POS-tag n-grams ($n < 5$, see Aarts et al. 1998; Borin et al. 2004).

POS-tag-chains which show a significant overuse/underuse for a special L1 or subgroup of L1s indicate transfer effects.
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- Only short token-based n-grams have been looked at!
Exploiting stylometry to uncover transfer

- A set of studies use machine learning techniques to classify the L1 of the author of IL-texts (ICLE version 1/2)

**Transfer effects on classification**

If learner text shows special features unique to just one L1-group and distinct from all other L1s, this must be due to transfer (if all other group variables are equally distributed).

- Koppel et al. (2003); Koppel et al. (2005); Tsur et al. (2007); JojoWong et al. (2009); Golcher (to appear)
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  - L1: Bulgarian, Czech, French, Russian, Spanish
  - L2: English
  - measures based on: errors, function words, rare POS-bi-grams, letter-bi-grams (sub-token)
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L1 specific structures in the IL were strong enough to recover the L1 highly above the baseline. \(\Rightarrow\) **transfer can be detected by L1-classification.**
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(Humboldt-Universität zu Berlin)  Stylometry & transfer in Falko
From similarity to transfer

We want to classify IL-texts for author’s L1:

- We define a similarity measure for texts:
  - A text is a string of characters.
  - Take two texts $A$ and $B$, compute a number $S$ from them.
  - Interpret this number as an indicator for similarity.

- Assign a text to the “most similar” L1 (details later!)

\[
\text{a posteriori justification}
\]

If the assignments are correct,

\[ \Rightarrow \text{then } S \text{ is a reflection of } L1 \text{ specific structures in IL (} \Leftarrow \text{ transfer}). \]
From similarity to transfer

Transfer on different linguistic levels

- L1 classification results based on different linguistic levels reflect transfer on that specific level
  - lemma $\Rightarrow$ (mainly) transfer on lexical choice
  - Part-of-Speech $\Rightarrow$ (mainly) syntactic transfer
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Transfer and grammatical errors

- If there is a difference between those results for
  (a) the learner text
  (b) a grammatically corrected version of it (target hypothesis)
  then this reflects transfer leading to ungrammatical IL-structures.
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Falko¹ - Error annotated corpus of advanced learners of German (Lüdeling et al. 2008)

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- L2 essay: 122,789 tokens & L1 essay: 68,485 tokens

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(Humboldt-Universität zu Berlin) Stylometry & transfer in Falko
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  - largest: Danish, English, Russian, French, Uzbek, Turkish
- 4 different essay topics (*titles*)
  - feminism, wages, criminality, university degree

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Falko data subset for classification

Texts included
- languages with at least 10 texts
- learners with only one L1

Very small data sample
We use only \( \approx 66,000 \) tokens. This is 34% of Falko.

<table>
<thead>
<tr>
<th>L1</th>
<th># of texts</th>
</tr>
</thead>
<tbody>
<tr>
<td>German (deu)(^a)</td>
<td>10</td>
</tr>
<tr>
<td>English (eng)</td>
<td>42</td>
</tr>
<tr>
<td>Danish (dan)</td>
<td>37</td>
</tr>
<tr>
<td>French (fra)</td>
<td>14</td>
</tr>
<tr>
<td>Russian (rus)</td>
<td>10</td>
</tr>
<tr>
<td>Turkish (tur)</td>
<td>10</td>
</tr>
<tr>
<td>total</td>
<td>126 texts</td>
</tr>
</tbody>
</table>

\(^a\) control group, excluded if sensible

<table>
<thead>
<tr>
<th>title</th>
<th>texts</th>
<th>texts</th>
</tr>
</thead>
<tbody>
<tr>
<td>“crime”</td>
<td>11</td>
<td>Kriminalität zahlt sich nicht aus.</td>
</tr>
<tr>
<td>“feminism”</td>
<td>23</td>
<td>Der Feminismus hat den Interessen der Frauen mehr geschadet als genützt.</td>
</tr>
<tr>
<td>“wages”</td>
<td>60</td>
<td>Die finanzielle Entlohnung eines Menschen sollte dem Beitrag entsprechen, den er/ sie für die Gesellschaft geleistet hat.</td>
</tr>
<tr>
<td>“studies”</td>
<td>32</td>
<td>Die meisten Universitätsabschlüsse sind nicht praxisorientiert und bereiten die Studenten nicht auf die wirkliche Welt vor.</td>
</tr>
</tbody>
</table>
Falko - 6 representations

- We have 6 representations of each text.
- Each representation is defined by two variables:

1. Level of linguistic representation:
   - Token or original texts:
     Man denke an den unterschiedlichen Grupp en, die sich für den Umw eltsschutz einsetzen.
   - Part-of-Speech tag sequence (TreeTagger):
     PIS VVFIN APPR ART ADJA NN $, PRELS PRF APPR ART NN VVINF $.
   - Lemma sequence:
     man denken an der unterschiedlichen Grupp e, der|es|sie für den Umw eltsschutz einsetzen.

2. Level of error contamination:
   - Learner raw learner texts:
     Man denke an den unterschiedlichen Grupp en, die [. . . ]
   - Target hypothesis the grammaticalized version (Reznicek et al. 2010):
     Man denke an die unterschiedlichen Grupp en, die [. . . ]

\(^1\)Schmid 1994.
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  1. Level of linguistic representation:
     - *token* original texts:
       Man denke an den unterschiedlichen Gruppen, die sich für den Umweltsschutz einsetzen.
     - *POS* Part-of-Speech tag sequence (Treetagger\(^1\)):
       PIS VVFIN APPR ART ADJA NN $,$, PRELS PRF APPR ART NN VVINF $.$
     - *lemma* lemma sequence:
       man denken an d unterschiedlich Gruppe , d er|es|sie für d Umweltsschutz einsetzen .

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       Man denke an den unterschiedlichen Gruppen, die [...]
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$S$ explained by example

Two very short texts:

\[ S = \sum \]
The similarity measure $S$ – basic concept

S explained by example

Two very short texts:

<table>
<thead>
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<th>$A = xabaya$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
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<th>$A = xabay$</th>
<th>$B = bcbabd$</th>
</tr>
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$S = \sum_{i=1}^{3} \log_2(i + 1)$

An important feature:

⇒ No maximal length is set (as is the usual practice).

⇒ No other information than (character) string repetitions are used.

(Humboldt-Universität zu Berlin) Stylometry & transfer in Falko QITL 4
**S explained by example**

Two very short texts:

<table>
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<th>substrings</th>
<th>$A = \text{xabay}$</th>
<th>$B = \text{bcbabd}$</th>
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\[
\begin{align*}
\log(2 \cdot 1 + 1) &= 1.09 \\
\log(1 \cdot 1 + 1) &= 0.69 \\
\log(1 \cdot 3 + 1) &= 1.39 \\
\end{align*}
\]

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*S explained by example*

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</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
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$\log(1 \cdot 1 + 1) = 0.69$  
$\log(1 \cdot 3 + 1) = 1.39$  
$\log(1 \cdot 0 + 1) = 0.0$  

An important feature:

All substrings of all lengths contribute:  
⇒ No maximal length is set (as is the usual practice).  
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**The similarity measure \( S \) – basic concept**

### **S explained by example**

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\]

\[
\log(1) \cdot 3 + 1 = 1.39
\]

\[
\log(1) \cdot 0 + 1 = 0
\]

\[
S = \sum 3.17
\]

An important feature

All substrings of all lengths contribute.

⇒ No maximal length is set (as is the usual practice).

No other information than (character) string repetitions are used.

(Humboldt-Universität zu Berlin)  
Stylometry & transfer in Falko
**S explained by example**

Two very short texts:

<table>
<thead>
<tr>
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<th>$A = xaby$</th>
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<tbody>
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The similarity measure $S$ – basic concept

$S$ explained by example

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</table>

$S = \sum \log (1 \cdot 1) = 0.69$

$A_2^1 = \log (2 \cdot 1) = 1.09$

$B_2^1 = \log (1 \cdot 1) = 0.69$

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\[
S = \sum \log (2^1 + 1^1) = 1.09
\]

\[
\log (1^1 + 1^1) = 0.69
\]

\[
\log (1^3 + 1^1) = 1.39
\]

\[
\log (1^0 + 1^1) = 0
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An important feature:

All substrings of all lengths contribute:

$⇒$ No maximal length is set (as is the usual practice).

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The similarity measure $S$ – basic concept

### $S$ explained by example

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</tr>
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</tr>
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$S = \sum$ is an important feature

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**$S$ explained by example**

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\[
\begin{align*}
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\text{log}(1 \cdot 1 + 1) &= 0.69 \\
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\text{log}(1 \cdot 0 + 1) &= 0
\end{align*}
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\[
\sum = 3.17
\]
S explained by example

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\[ S = \sum = 3.17 \]
The similarity measure $S$ – basic concept

$S$ explained by example

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</table>

$S = \sum = 3.17$

an important feature

All substrings of all lengths contribute:

$\Rightarrow$ No maximal length is set (as is the usual praxis).

No other information than (character) string repetitions are used.
S as an established stylometric measure

Various stylometric tasks have been investigated with S:

- **Translationese**: Have translations their own “style”?
  - Studies in Baroni et al. (2006) have been replicated.

- **Authorship Attribution**: Who wrote the federalist papers? (Golcher 2007)
  - Main stream attribution of disputed essays confirmed.

- **Recovery of L1 in English**:
  - Replication of the mentioned studies Tsur et al. (2007); Koppel et al. (2005) (Golcher 2007; Golcher to appear)
1 Research Questions: Joining two points of view

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A short reminder of the data.
Falko data subset for classification

**Texts included**
- languages with at least 10 texts
- learners with only one L1

**Very small data sample**
We use only $\approx 66,000$ tokens. This is 34% of Falko.

<table>
<thead>
<tr>
<th>L1</th>
<th># of texts</th>
</tr>
</thead>
<tbody>
<tr>
<td>German</td>
<td>(deu)$^a$ 10</td>
</tr>
<tr>
<td>English</td>
<td>(eng) 42</td>
</tr>
<tr>
<td>Danish</td>
<td>(dan) 37</td>
</tr>
<tr>
<td>French</td>
<td>(fra) 14</td>
</tr>
<tr>
<td>Russian</td>
<td>(rus) 10</td>
</tr>
<tr>
<td>Turkish</td>
<td>(tur) 10</td>
</tr>
<tr>
<td><strong>total</strong></td>
<td><strong>126 texts</strong></td>
</tr>
</tbody>
</table>

$^a$ control group, excluded if sensible

<table>
<thead>
<tr>
<th>Title</th>
<th>Texts</th>
<th>Texts</th>
</tr>
</thead>
<tbody>
<tr>
<td>“crime”</td>
<td>11</td>
<td>Kriminalität zahlt sich nicht aus.</td>
</tr>
<tr>
<td>“feminism”</td>
<td>23</td>
<td>Der Feminismus hat den Interessen der Frauen mehr geschadet als genützt.</td>
</tr>
<tr>
<td>“wages”</td>
<td>60</td>
<td>Die finanzielle Entlohnung eines Menschen sollte dem Beitrag entsprechen, den er/ sie für die Gesellschaft geleistet hat.</td>
</tr>
<tr>
<td>“studies”</td>
<td>32</td>
<td>Die meisten Universitätsabschlüsse sind nicht praxisorientiert und bereiten die Studenten nicht auf die wirkliche Welt vor.</td>
</tr>
</tbody>
</table>
Remark

There is no significant correlation between the essay title and the author’s L1.
Some details of the classification method

- Take one text $T_i$ after another as test text (126 texts).
- following steps:
  1. Compute $S(T_i, T_j)$ for the remaining 125 training texts ($i \neq j$)
  2. Group those $S$ values according to the $L1$ of those training texts.
  3. Compute the mean $S$ value $\bar{S}_{L1}$ for each $L1$ group.
  4. Assign the test text $T_i$ to the $L1$ group with the highest $\bar{S}_{L1}$. 
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Proof of concept

**Expectation 1**

The baseline of random assignments is around \( \frac{126}{6} = 21 \).
We expect to be substantially better than this baseline.
**Proof of concept**

**Expectation 1**

The baseline of random assignments is around $126/6 = 21$. We expect to be substantially better than this baseline.

**Outcome**

With the raw learner texts we get 65 correct assignments out of 126. ⇒ There is something meaningful going on.
A short reminder of the different representations of Falko.
Falko - 6 representations

- We have 6 representations of each text.
- Each representation is defined by two variables:
  1. Level of linguistic representation:
     - **token** original texts:
       Man denke an den unterschiedlichen Gruppen, die sich für den Umweltsschutz einsetzen.
     - **POS** Part-of-Speech tag sequence (Treetagger\(^1\)):
       PIS VVFIN APPR ART ADJA NN $, PRELS PRF APPR ART NN VVINF $.
     - **lemma** lemma sequence:
       man denken an d unterschiedlich Gruppe , d er|es|sie für d Umweltsschutz einsetzen .
  2. Level of error contamination:
     - **learner** The raw learner texts:
       Man denke an den unterschiedlichen Gruppen, die […]
     - **Target hypothesis** the grammaticalized version(Reznicek et al. 2010):
       Man denke an die unterschiedlichen Gruppen, die […]

\(^1\)Schmid 1994.
L1 classification

Expectation 2

Token representation shows a stronger L1 effect than lemma.
Because: lemma ignores morphology completely.
**L1 classification**

**Expectation 2**

*token* representation shows a stronger L1 effect than *lemma*.

Because: *lemma* ignores morphology completely.

**Figure:** German L1 texts are disregarded here.
L1 classification

Expectation 2

token representation shows a stronger L1 effect than lemma.

Because: lemma ignores morphology completely.

Outcome: Big surprise

We could not detect a morphology effect.

Figure: German L1 texts are disregarded here.
L1 classification

<table>
<thead>
<tr>
<th>Text</th>
<th>tok</th>
<th>POS</th>
<th>Lemma</th>
<th>Classification accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>59</td>
<td>48</td>
<td>60</td>
<td>baseline (Monte carlo simulated)</td>
</tr>
<tr>
<td></td>
<td>54</td>
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**Figure:** German L1 texts are disregarded here.
L1 classification

Figure: German L1 texts are disregarded here.

**Expectation 3**

The grammaticalized *target hypothesis* should score somewhat lower than the *learner* version.
L1 classification

Figure: German L1 texts are disregarded here.

Expectation 3

The grammaticalized target hypothesis should score somewhat lower than the learner version.

Outcome

True.
Grammatical error correction lowers accuracy consistently but only minimally.

That’s not bad, but didn’t we miss some source of similarity?
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Another possible influence: Content

- Until now we ignored the essay title people wrote about.
- Obviously, texts about “crime” will share words.
- This of course leads to higher $S$ values.
- If this title effect is larger than the L1 effect, the latter will be masked.
This is not a newly discovered problem

- This issue is well known from stylometric studies (e.g. Baroni et al. 2006).
- There, usually “content words” are removed. (or similar).
- Rarely any quantitative investigation is tried (but see Clement et al. 2003)

So, how large is this effect? That’s what we turn to now...
The same thing with another variable

Now we classify the texts according to essay title, instead of L1.
classification according to *title*

**Expectation 4**

We expect a strong *title* effect in the *token* and *lemma* representations.
classification according to \textit{title}

**Expectation 4**

We expect a strong \textit{title} effect in the \textit{token} and \textit{lemma} representations.

**Expectation 5**

We do not expect a \textit{title} effect in the \textit{POS} representation.
classification according to \textit{title}

\begin{itemize}
\item \textbf{Expectation 4}
  \textit{We expect a strong title effect in the \textit{token} and \textit{lemma} representations.}
\item \textbf{Expectation 5}
  \textit{We do not expect a title effect in the POS representation.}
\end{itemize}
classification according to title

**Expectation 4**
We expect a strong title effect in the token and lemma representations.

**Outcome**
nearly perfect.

**Expectation 5**
We do not expect a title effect in the POS representation.
classification according to title

Expectation 4
We expect a strong *title* effect in the *token* and *lemma* representations.

Outcome
nearly perfect.

Expectation 5
We do not expect a *title* effect in the *POS* representation.

Outcome: Surprise.
Also from the *POS* representation we can recover the essay *title*.
A simple heuristic for filtering out essay title

- We divide all $S(A, B)$ in two groups:
  1. $A$ and $B$ have the same title.
  2. They have not.
- We compute the mean of each group.
- Each $S$ value is divided by the mean of its group.
Classification results before averaging out *title*

**Expectation 6**

If we filter out the essay *title*, L1-classification improves.
Classification results before averaging out *title*

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**Figure:** German L1 texts are disregarded here.
Classification results after averaging out *title*

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If we filter out the essay *title*, L1-classification improves.

((Humboldt-Universität zu Berlin) Stylometry & transfer in Falko QITL 4 42 / 76)
Classification results after averaging out title

Expectation 6

If we filter out the essay title, L1-classification improves.

Outcome

True.

Figure: German L1 texts are disregarded here.
Classification results after averaging out title

Expectation 6
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Outcome
True.

Discussion:

Figure: German L1 texts are disregarded here.
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1. transfer on lexical choice is much stronger than on syntax. (lemma > POS)

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Expectation 6
If we filter out the essay title, L1-classification improves.

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Discussion:
1. Transfer on lexical choice is much stronger than on syntax. (lemma > POS)
2. We still see no effect of morphology. (lemma = tok)

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Copied material

Texts about the same subject will normally share lexical material. We have an additional problem:

- The full title we call “feminism” reads as
  
  \textit{Der Feminismus hat} \textit{den Interessen der Frauen mehr geschadet als genützt.}

  \textit{Feminism damaged the interests of the women rather than it helped them.}

- Especially learners tend to copy phrases like “\textit{den Interessen der Frauen}”.

- These long shared substrings make unproportional contributions to $S$. 

explosion of substrings

The number of substrings of a string grows quadratically with its length.
Expectation

Expectation 5
If we remove copied material we improve classification performance.

- yes, we can remove copied material.
Definition of “copied material”

We use a simple heuristic to identify copied material

**Definition (copied material)**

A string in text $B$ is copied from text $A$, if

- it occurs only once in the source text $A$.
- this is true even if we strip $n$ characters at both sides.

**Example (set $n$ to 1)**

- $A$ Do we have beer or do we have wine, Josef?
- $B$ Someone must have been telling lies about Josef K.

applying the definition:

- “Josef” is copied.
- “have b” is not (“have” occurs twice in text $A$)
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- “Josef” is copied.
- “have b” is not (“have” occurs twice in text A)
Example

\[ n = 2 \]

Zum Schluss glaube ich, dass der Feminismus den Interessen der Frauen sehr viel nützen könne, aber es gibt zu viele Leute, die die Konzepte des Feminismus schaden, wenn sie dem Feminismus für falschen Gründen oder in den falschen Situationen nützen.

At the end I think, that feminism could help the interests of the women very much, but there are too many people, which harm them concepts of feminism, if they help femininism for wrongs reasons or in wrong situations.
Example

\[ n = 5 \]

Zum Schluss glaube ich, dass der Feminismus den Interessen der Frauen sehr viel nützen könne, aber es gibt zu viele Leute, die die Konzepte des Feminismus schaden, wenn sie dem Feminismus für falschen Gründen oder in den falschen Situationen nützen.

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Example

$\quad n = 10$

Zum Schluss glaube ich, dass der Feminismus den Interessen der Frauen sehr viel nützen könne, aber es gibt zu viele Leute, die die Konzepte des Feminismus schaden, wenn sie dem Feminisumus für falschen Gründen oder in den falschen Situationen nützen.

At the end I think, that feminism could help the interests of the women very much, but there are too many people, which harm them concepts of feminism, if they help femininism for wrongs reasons or in wrong situations.
An optimum for the parameter $n$

- Removing copied material helps identifying L1.
- An approximate optimum is $n = 10$.
- *Title* identification is not hampered.
- Filtering more and more data damps *title* and L1 effect.
1. Research Questions: Joining two points of view

2. Background SLA
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   - Transfer

3. Learner Corpus Research on transfer

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   - Road map
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5. The similarity measure $S$ – basic concept

6. Classification according L1
   - Preliminary results
   - Taking the essay *title* into account
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7. Beyond stylistometry, beyond classification

8. Conclusion
Compared classification results

- Title unaccounted for: 65 = 52%
- Title averaged out: 74 = 59%
- Copies removed: 84 = 67%

Baseline (Monte carlo simulated)
Expectation

Expectation 5
If we remove copied material we improve classification performance.

Outcome
This is indeed the case.
# Distribution of right and wrong classifications

![Table and Diagram]

**Figure:** Raw text.
Distribution of right and wrong classifications

Figure: title averaged out.
Distribution of right and wrong classifications

**Figure:** copied material removed.
Distribution of right and wrong classifications

1. **German** is detected with 100% accuracy.

**Figure:** copied material removed.
Distribution of right and wrong classifications

<table>
<thead>
<tr>
<th>classified as</th>
<th>dan</th>
<th>deu</th>
<th>eng</th>
<th>fra</th>
<th>rus</th>
<th>tur</th>
<th>real L1</th>
</tr>
</thead>
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<td>6</td>
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<td>3</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>23  22  29  15  16  21  126</td>
</tr>
</tbody>
</table>

1. German is detected with 100% accuracy.
   - IL has been claimed to be more variable. (see Romaine 2003)

Figure: copied material removed.
Distribution of right and wrong classifications

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3. **Turkish** behaves a bit erratic.
   - Those were the most ungrammatical texts.

**Figure**: copied material removed.
Beyond stylometry, beyond classification

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Where to go from here?

- Successful classification is a reliable indicator for existing transfer.  
  but effect sizes can’t be readily quantified.
- The *title* effect seems to be “stronger” than L1.  
  but how much?  
  ⇒ comparison of classification accuracies is rather indirect.

Can we surpass the *stylometric* classificational view?

1. Can we directly quantify the influence of *title* and L1?
2. Can we directly compare them? For different levels of representation?
For each $S(A, B)$ we construct two variables:

- `sameTitle` 1 if $A$ and $B$ share its title, 0 otherwise.
- `sameL1` 1 if authors of $A$ and $B$ share $L1$, 0 otherwise.

Now we set up a model

$$S = \alpha \cdot sameTitle + \beta \cdot sameL1 + <text\_specific\_contribution> + \epsilon$$

where $\epsilon$ is a normally distributed error term.
Building a (linear mixed) model

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$$S = \alpha \cdot sameTitle + \beta \cdot sameL1 + \text{<textspecific contributions>} + \epsilon$$

where $\epsilon$ is a normally distributed error term.

- This (linear mixed) model is fitted.
- The parameters $\alpha$ and $\beta$ can be compared.
The results

- **Observations**
  1. *essay title* always stronger than \( \text{L1} \): All points below 1.
  2. Again, no difference between *token* and *lemma*.
  3. The \( \text{L1} \) influence in *POS* is much more pronounced.
  4. Removing errors (slightly) weakens \( \text{L1} \) influence.

**Figure:** \( \text{L1} (\beta) \) divided by *title* (\( \alpha \)) effect.
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What comes out for stylometry

- Stylometric L1 classification is rather successful:
  - Remember how small the data are (66,000 tokens).
  - The method is simple and intuitive.
  - Only substrings, but all substrings are used.

- We can quantify the effects of L1 and title or content.

- Removal of
  1. title influence
  2. copied material

  greatly boosts L1 classification.

That is: S effectively measures L1 induced similarity of learner texts.
What comes out for learner corpus research

1. The presented similarity measure can be used to detect transfer effects.
2. The transfer effect on lexical choice seems considerably stronger than on syntax.
3. Morphological transfer seems to play no significant role in our data.
4. The amount of transfer leading to ungrammaticality seems to be minor.

Warning!
- Learner corpus studies widely ignore the influence of the essay subject (*title*).
- But it’s even quite strong on abstract levels such as the Part-of-Speech representation.
Open questions

1. Which substrings in which representation contribute most to the transfer related similarity?

   *It is possible to scan the texts character by character and check which contributes what.*
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5. How good are the classification results, if all levels are used in combination?
Thank you


Literatur


Literatur VI


9 Norming S

10 Density plots
An obvious problem

The similarity measure $S$ as a formula

$$S(A, B) = \sum_{\text{all substrings } s} \log(F_A(s)F_B(s) + 1)$$

$F_A(s)$ – Frequency of substring $s$ in Text $A$

- Longer texts $\Rightarrow$ more and more frequent substrings.
- $S$ grows with text length!
- Length dependency not easy to parametrize.
- and that would not be the full story...
- An working heuristic is applied.
A life example

- Eight Dutch authors\(^a\).
- One training file / one test file.
- Each training file compared with each test file.

\[
\Rightarrow \text{Training File 8 is the shortest one.}
\]

\[
\Rightarrow \text{Darkest column.}
\]

\[
\Rightarrow \text{lowest } S \text{ values.}
\]

\(^a\)Juola 2004.

**Figure:** Dark: low \(S\)-values; Light: high \(S\)-values.

**Simple:** Dividing Columns by their mean.
Averaging out single text dependencies

This normed version of $S$ is what we really used.
Norming S

Density plots
Distribution of $S(A, B)$ values

**Green:** $A$ and $B$ share *title* or L1

**Red:** Different *title* or L1.

**Same *title* or not?**

**Same L1 or not?**

- *title* much stronger than L1.
- But similarity due to L1 is what we are interested in.
Distribution of $S(A, B)$ values after averaging out *title*

Again: **Green**: $A$ and $B$ share L1; **Red**: Different L1.

- The difference is much clearer now.
- Classification jumps from 65 to 74 correct decisions (out of 126).
Distribution of $S(A, B)$ values after averaging out *title*

Again: **Green**: $A$ and $B$ share $L1$; **Red**: Different $L1$.

- The difference is much clearer now.
- Classification jumps from 65 to 74 correct decisions (out of 126).
- Suspiciously stretched right tail.
Distribution of $S(A, B)$ values after averaging out *title*

Again: **Green:** $A$ and $B$ share $L1$; **Red:** Different $L1$.

with *title*:

- The difference is much clearer now.
- Classification jumps from 65 to 74 correct decisions (out of 126).
- Suspiciously stretched right tail. $\Rightarrow$ To this we turn now.
Density plots after removing copied material

The right tail is greatly reduced.

Classification results again jump from 74 to 84 correct (from 126).