Performance of linking researchers to theses

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Note: the "usable" links are saved to the db in $src/dataprep/main/link/prep_linked_data.py$	9
This script makes some plots of the advisor links and saves the most plausible links to a table in the database	se.
t parameters for selecting links	
in_score_advisors <- 0.7 # minimum score from dedupe	

```
max_year_diff <- 5 # maximum difference between advisory and own publication at institution. 5 is arbit
max_uniname_distance <- 0.02 # keep only links where the jarowinkler distance between the institution n
```

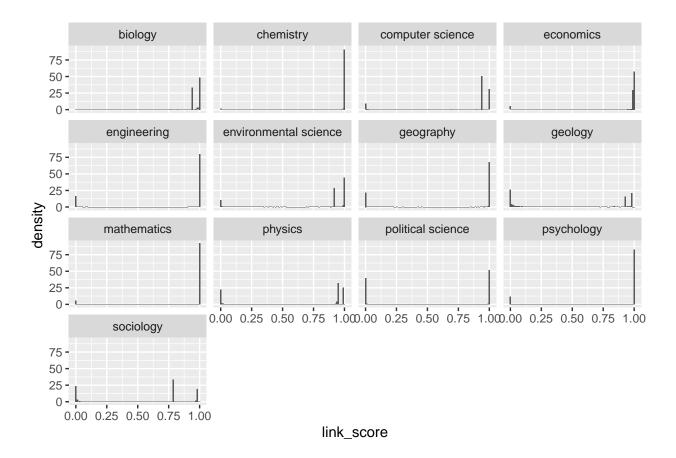
Overview

```
current_links <- collect(current_links)</pre>
linked_advisors <- collect(linked_advisors)</pre>
theses <- collect(theses)</pre>
authors_affiliation <- collect(authors_affiliation)</pre>
linking_info <- collect(linking_info)</pre>
pq_fields_mag <- collect(pq_fields_mag)</pre>
```

Linking scores

• conditioning on link score > 0.7 is fine

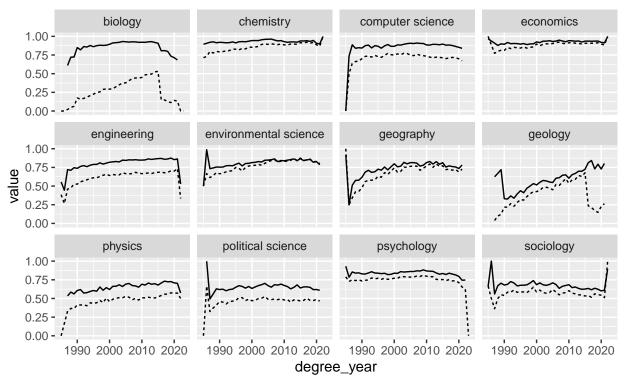
```
linked_advisors %>%
  left_join(linking_info, by = "iteration_id") %>%
  ggplot(aes(x = link_score)) +
  geom_histogram(bins = 100, aes(y = ..density..)) +
  facet_wrap(~field)
```



Link performance by graduation year

- fraction of listed advisors where the link_score is above the treshold
- the mean link score for advisors where dedupe finds a link (link score is not NA)
- NOTE: the field here is assigned based on the first reported in the dissertation, and the crosswalked to the MAG field
 - in the figure above, we used the field from iteration_id, but this only works for advisors that dedupe suggests to be a link

Warning: Removed 2 row(s) containing missing values (geom_path).



stat — mean_score --- share_linked

```
2 asim
                dasgupta university of california los angeles
                                                                       1990
## 3 barry s
                cooperman university of pennsylvania
                                                                       1996
                                                                                5
## 4 bob g
                sanders
                          university of texas at austin
                                                                       1998
                                                                                5
## 5 douglas e eveleigh rutgers university
                                                                                5
                                                                       1993
   6 michael
                freeling university of california berkeley
                                                                       1997
                                                                                5
  7 mingdaw
                tsai
                          ohio state university
                                                                                5
##
                                                                       1997
  8 naba k
                          university of nebraska lincoln
                                                                                5
                gupta
                                                                       1997
                          university of southern california
                                                                                5
## 9 norman
                arnheim
                                                                       1993
## 10 paul f
                cook
                          university of north texas
                                                                       1993
                                                                                5
# score by year %>% filter(lastname == "dasqupta" & firstname == "asim" & !is.na(iteration id)) # never
# score_by_year %>% filter(lastname == "freeling" & firstname == "michael") # never linked
# scale this up? check all the main fields of the authors with such names? -- tedious
```

Notes

- Reasons for why advisor not linked
 - they are not sampled for linking either in the mag or proquest data
 - * most plausibly because they are assigned to different fields
 - institution names do not overlap
 - dedupe does not find a link even though it should
 - * but how can it explain the time trend?
- Comparing fields in MAG and ProQuest dissertations
 - General
 - * not linking an advisor in biology does not mean do not link them in chemistry if the thesis is also classified in chemistry
 - * in the data above, this happens if biology is listed at position 0
 - Biology
 - * main field chemistry: gerlt, cooperman, eveleigh (two of them with long careers, but both in chemistry), tsai
 - * main field biologe: dasgupta, freeling
 - * at least one of the dissertations of freeling are sampled for the linking
 - Sociology
 - * different main field: ishisaka, coulton (medicine), howell (geography), mindel (psychology)
 - * not in MAG, but findable on google: khleif, gullerud
 - * not in MAG, not findable on google: liff
- Next steps
 - widen the sampled field in MAG
 - re-train and re-check

Here is some python code to look at the learned settings, based on

- \bullet https://github.com/dedupeio/rlr/blob/master/rlr/lr.py (new dedupe does not use this anymore I think)
- $\bullet \ \, \text{https://github.com/dedupe/blob/5742efc7fc696c06d3327e038541532e584551a8/dedupe/api.} \, \, \text{pv} \\$
- Note: The predicates are similar for all three fields I looked at. I do not know how the weights correspond to the logit regression coefficients

```
sf_biology = "/mnt/ssd/DedupeFiles/advisors/settings_biology_1985_2022_institutionTrue_fieldofstudy_cat.
sf_chemistry = "/mnt/ssd/DedupeFiles/advisors/settings_chemistry_1985_2022_institutionTrue_fieldofstudy
sf_cs = "/mnt/ssd/DedupeFiles/advisors/settings_computer_science_1985_2022_institutionTrue_fieldofstudy
with open(sf_biology, "rb") as sf:
```

```
linker_biology = dedupe.StaticRecordLink(sf)

with open(sf_chemistry, "rb") as sf:
    linker_chemistry = dedupe.StaticRecordLink(sf)

with open(sf_cs, "rb") as sf:
    linker_cs = dedupe.StaticRecordLink(sf)

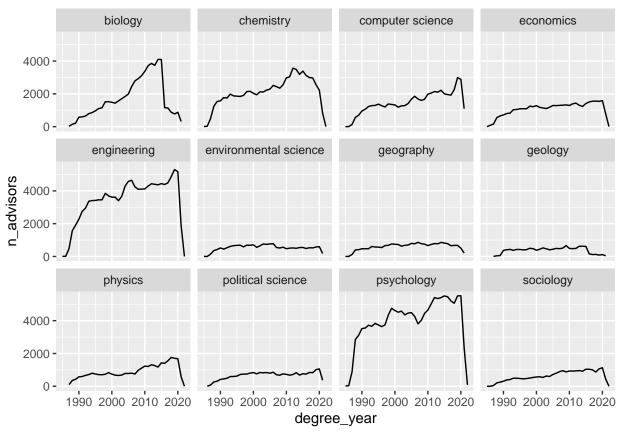
linker_biology.predicates
linker_chemistry.predicates
linker_cs.predicates

linker_cs.predicates

linker_biology.classifier.weights
linker_chemistry.classifier.weights
linker_cs.classifier.weights
```

Number of linked advisors

• not sure this is still relevant?



old comments

• for instance, a student of michael j lambert (authorid 2120159045; relationship id 303670971_0 in proquest) from pre-1990 is link score of 0.02, but should be a clear link

Compare number of links across iterations within fields

```
fields_iter_compare <- c("economics", "chemistry")</pre>
min_score <- 0.8
keep_iter_ids <- tbl(con, "linking_info_advisors") %>%
  filter(field %in% fields_iter_compare) %>%
  filter(testing == 0) %>%
  collect() %>%
  group_by(field, train_name) %>%
  arrange(iteration_id) %>%
  mutate(nb = n(),
         id = row_number()) %>%
  ungroup() %>%
  filter(id == nb) %>%
  select(iteration_id, field, train_name)
linked_ids_to_compare <- tbl(con, "linked_ids_advisors") %>%
  inner_join(
   tbl(con, "linking_info_advisors") %>%
      filter(field %in% fields_iter_compare),
   by = "iteration_id"
```

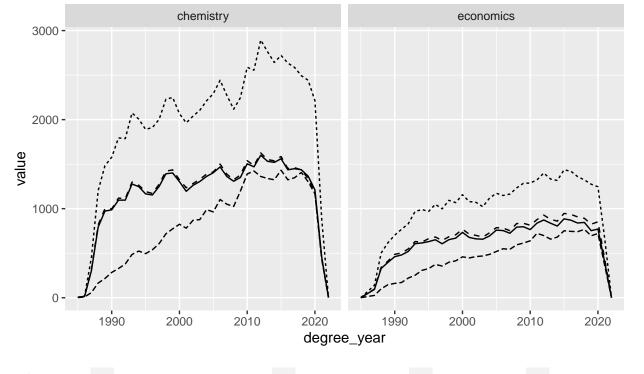
```
) %>%
inner_join(
  tbl(con, "pq_advisors") %>%
    select(relationship_id, goid),
  by = "relationship_id"
) %>%
inner_join(
  tbl(con, "pq_authors") %>%
    select(goid, degree_year),
  by = "goid"
) %>%
collect() %>%
filter(iteration_id %in% keep_iter_ids$iteration_id)
```

Number of graduates with at least 1 advisor

```
d_sum <- linked_ids_to_compare %>%
  filter(link_score >= min_score) %>%
  group_by(train_name, field, degree_year) %>%
  summarise(n_advisors = n(),
            n_graduates = n_distinct(goid),
            .groups = "drop") %>%
  pivot_longer(cols = starts_with("n_"), names_to = "variable")
plotvars <- c("n_graduates")</pre>
map(.x = plotvars,
    .f = ~d_sum \%
     filter(variable == .x) %>%
      ggplot(aes(x = degree_year, y = value)) +
      geom_line(aes(linetype = train_name)) +
      facet_wrap(~field) +
      theme(legend.position = "bottom") +
      labs(title = paste0("Count: ", .x))
```

[[1]]

Count: n_graduates



train_name — christoph_baseline_update --- christoph_degree0 --- flavio_baseline -- flavio_baseline

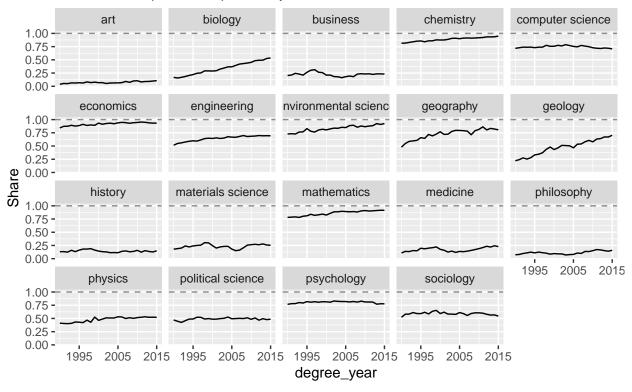
Fraction of theses with at least 1 supervisor linked to MAG

```
s_thesis_advisor_link <- theses %>%
 filter(degree_year %in% 1990:2015) %>%
  left_join(linked_advisors %>%
              filter(link_score > min_score_advisors) %>%
              select(relationship_id) %>%
              mutate(linked = 1),
            by = "relationship_id") %>%
  mutate(linked = ifelse(is.na(linked), 0, linked)) %>%
  group_by(goid) %>%
  mutate(any_link = max(linked)) %>%
  ungroup() %>%
  filter(!duplicated(goid)) %>%
  group_by(degree_year, any_link, fieldname0_mag) %>%
  summarise(n_{theses} = n(),
            .groups = "drop") %>%
  group_by(degree_year, fieldname0_mag) %>%
  mutate(s = n_theses / sum(n_theses)) %>%
  ungroup() %>%
  filter(any_link == 1)
s_thesis_advisor_link %>%
  ggplot(aes(x = degree_year, y = s)) +
  geom line() +
 facet_wrap(~fieldname0_mag) +
  scale_x_continuous(breaks = c(1995, 2005, 2015)) +
```

```
geom_hline(yintercept = 1, color = "grey55", linetype = "dashed") +
labs(y = "Share", title = "Share of US theses with >=1 supervisor linked to MAG",
subtitle = "Where >= 1 supervisor reported; by first indicated field0 of thesis.")
```

Share of US theses with >=1 supervisor linked to MAG

Where >= 1 supervisor reported; by first indicated field0 of thesis.



Notes

- Idea: since supervisors tend to be established researchers and publish regularly, we should find a large fraction of supervisors reported in ProQuest in the MAG data.
- The split by field is not exact because the link may have been found using a different reported field0.
- The close to 100% is reassuring of the MAG data quality on affiliations in these fields.
- Fields of concern: physics, sociology, poli science, biology (the level, the break and the trend).

Note: the "usable" links are saved to the db in src/dataprep/main/link/prep_linked_data.py