

Tidymodels

```
library(tidymodels)
```

```
## Registered S3 method overwritten by 'tune':
```

```
##   method                from
```

```
##   required_pkgs.model_spec parsnip
```

```
## — Attaching packages ————— tidymodels 0.1.4 —
```

```
## ✓ broom          0.7.10    ✓ rsample          0.1.0
```

```
## ✓ dials          0.0.10    ✓ tune             0.1.6
```

```
## ✓ infer          1.0.0      ✓ workflows        0.2.4
```

```
## ✓ modeldata      0.1.1      ✓ workflowsets    0.1.0
```

```
## ✓ parsnip        0.1.7      ✓ yardstick       0.0.8
```

```
## ✓ recipes        0.1.17
```

```
## — Conflicts ————— tidymodels_conflicts() —
```

```
## x scales::discard() masks purrr::discard()
```

```
## x dplyr::filter()   masks stats::filter()
```

```
## x recipes::fixed() masks stringr::fixed()
```

```
## x dplyr::lag()      masks stats::lag()
```

```
## x rsample::populate() masks Rcpp::populate()
```

```
## x yardstick::spec() masks readr::spec()
```

```
## x recipes::step()   masks stats::step()
```

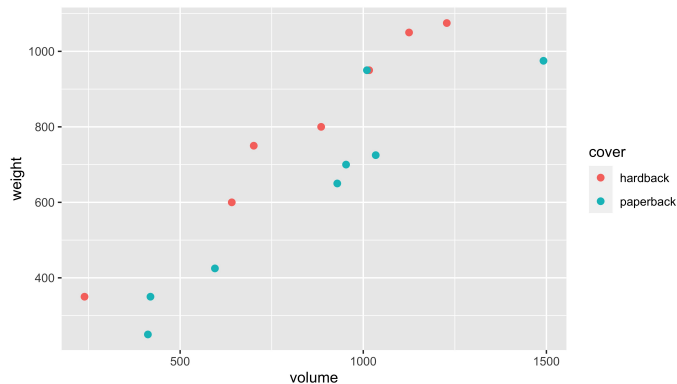
```
## • Dig deeper into tidy modeling with R at https://www.tmr.org
```

Book data

```
(books = DAAG::allbacks %>%  
  as_tibble() %>%  
  select(-area) %>%  
  mutate(  
    cover = forcats::fct_recode(  
      cover,  
      "hardback" = "hb",  
      "paperback" = "pb"  
    )  
  )  
)
```

```
## # A tibble: 15 × 3  
##   volume weight cover  
##   <dbl> <dbl> <fct>  
## 1     885     800 hardback  
## 2    1016     950 hardback  
## 3    1125    1050 hardback  
## 4     239     350 hardback  
## 5     701     750 hardback  
## 6     641     600 hardback  
## 7    1228    1075 hardback  
## 8     412     250 paperback
```

```
ggplot(books, aes(x=volume, y=weight, color = cov  
  geom_point(size=2)
```



Building a tidymodel

```
linear_reg()
```

```
## Linear Regression Model Specification (regression)
```

```
##
```

```
## Computational engine: lm
```

Building a tidymodel

```
linear_reg() %>%  
  set_engine("lm")
```

```
## Linear Regression Model Specification (regression)  
##  
## Computational engine: lm
```

Building a tidymodel

```
linear_reg() %>%  
  set_engine("lm") %>%  
  fit(weight ~ volume * cover, data = books)  
  
## parsnip model object  
##  
## Fit time: 10ms  
##  
## Call:  
## stats::lm(formula = weight ~ volume * cover, da  
##  
## Coefficients:  
##           (Intercept)           volume  
##           161.58654           0.76159  
## coverpaperback volume:coverpaperback  
##           -120.21407           -0.07573
```

```
lm(weight ~ volume * cover, data = books)  
  
##  
## Call:  
## lm(formula = weight ~ volume * cover, data = books)  
##  
## Coefficients:  
##           (Intercept)           volume  
##           161.58654           0.76159  
## coverpaperback volume:coverpaperback  
##           -120.21407           -0.07573
```

Tidy model objects



```
summary(lm(weight ~ volume * cover, data = books))
```

```
##
## Call:
## lm(formula = weight ~ volume * cover, data = books)
##
## Residuals:
##   Min     1Q  Median     3Q    Max
## -89.67 -32.07 -21.82  17.94 215.91
##
## Coefficients:
##              Estimate Std. Error t value
## (Intercept)    161.58654   86.51918   1.868
## volume           0.76159    0.09718   7.837
## coverpaperback -120.21407  115.65899  -1.039
## volume:coverpaperback -0.07573    0.12802  -0.592
##
##              Pr(>|t|)
## (Intercept)    0.0887 .
## volume         7.94e-06 ***
## coverpaperback 0.3209
## volume:coverpaperback 0.5661
## ---
## Signif. codes:
## 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 80.41 on 11 degrees of freedom
## Multiple R-squared:  0.9297, Adjusted R-squared:  0.9105
## F-statistic: 48.5 on 3 and 11 DF, p-value: 1.245e-06
```

```
lm_tm = linear_reg() %>%
  set_engine("lm") %>%
  fit(weight ~ volume * cover, data = books)
```

```
summary(lm_tm)
```

```
##           Length Class      Mode
## lvl         0   -none-    NULL
## spec        5   linear_reg list
## fit         13    lm       list
## preproc     1   -none-    list
## elapsed     5   proc_time numeric
```

```
broom::tidy(lm_tm)
```

```
## # A tibble: 4 × 5
##   term                estimate std.error statistic p.value
##   <chr>                <dbl>   <dbl>    <dbl>  <dbl>
## 1 (Intercept)          1.62e+2  86.5      1.87  8.87e-2
## 2 volume                7.62e-1  0.0972    7.84  7.94e-6
```

Tidy model statistics

```
broom::glance(lm(weight ~ volume * cover, data = books))
```

```
## # A tibble: 1 × 12
##   r.squared adj.r.squared sigma statistic   p.value    df
##   <dbl>      <dbl> <dbl>   <dbl>     <dbl> <dbl>
## 1    0.930      0.911  80.4    48.5 0.00000124    3
## # ... with 6 more variables: logLik <dbl>, AIC <dbl>,
## #   BIC <dbl>, deviance <dbl>, df.residual <int>,
## #   nobs <int>
```

```
broom::glance(lm_tm)
```

```
## # A tibble: 1 × 12
##   r.squared adj.r.squared sigma statistic   p.value    df
##   <dbl>      <dbl> <dbl>   <dbl>     <dbl> <dbl>
## 1    0.930      0.911  80.4    48.5 0.00000124    3
## # ... with 6 more variables: logLik <dbl>, AIC <dbl>,
## #   BIC <dbl>, deviance <dbl>, df.residual <int>,
## #   nobs <int>
```


Tidy model prediction

```
broom::augment(lm_tm, new_data = books)
```

```
## # A tibble: 15 × 5
##   volume weight cover   .pred .resid
##   <dbl> <dbl> <fct>   <dbl> <dbl>
## 1   885   800 hardback  836. -35.6
## 2  1016   950 hardback  935.  14.6
## 3  1125  1050 hardback 1018.  31.6
## 4   239   350 hardback  344.   6.39
## 5   701   750 hardback  695.  54.5
## 6   641   600 hardback  650. -49.8
## 7  1228  1075 hardback 1097. -21.8
## 8   412   250 paperback 324. -73.9
## 9   953   700 paperback 695.   5.00
## 10  929   650 paperback 679. -28.5
## 11 1492   975 paperback 1065. -89.7
## 12  419   350 paperback 329.  21.3
## 13 1010   950 paperback 734. 216.
## 14  595   425 paperback 449. -24.5
## 15 1034   725 paperback 751. -25.6
```

Putting it together

```
lm_tm %>%  
  augment(  
    new_data = tidyr::expand_grid(  
      volume = seq(0, 1500, by=5),  
      cover = c("hardback", "paperback") %>% as.factor()  
    )  
  ) %>%  
  rename(weight = .pred) %>%  
  ggplot(aes(x = volume, y = weight, color = cover, group = cover)) +  
    geom_line() +  
    geom_point(data = books)
```

Why do we care?



```
show_engines("linear_reg")
```

```
## # A tibble: 5 × 2
##   engine mode
##   <chr> <chr>
## 1 lm     regression
## 2 glmnet regression
## 3 stan   regression
## 4 spark  regression
## 5 keras  regression
```

```
(bayes_tm = linear_reg()) %>%
  set_engine(
    "stan",
    prior_intercept = rstanarm::student_t(df = 1),
    prior = rstanarm::student_t(df = 1),
    seed = 1234
  )
)
```

```
## Linear Regression Model Specification (regression)
##
## Engine-Specific Arguments:
##   prior_intercept = rstanarm::student_t(df = 1)
##   prior = rstanarm::student_t(df = 1)
##   seed = 1234
##
## Computational engine: stan
```

Fitting with `rstanarm`

```
(bayes_tm = bayes_tm %>%  
  fit(weight ~ volume * cover, data = books)  
)
```

```
## Warning: There were 19 divergent transitions after warmup. See  
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup  
## to find out why this is a problem and how to eliminate them.
```

```
## Warning: Examine the pairs() plot to diagnose sampling problems
```

```
## parsnip model object
```

```
##
```

```
## Fit time: 911ms
```

```
## stan_glm
```

```
## family: gaussian [identity]
```

```
## formula: weight ~ volume * cover
```

```
## observations: 15
```

```
## predictors: 4
```

```
## -----
```

```
##
```

	Median	MAD_SD
## (Intercept)	98.2	58.8
## volume	0.8	0.1
## coverpaperback	-0.3	3.5
## volume:coverpaperback	-0.2	0.1

```
##
```

```
## Auxiliary parameter(s):
```

```
## Median MAD_SD
```

```
## sigma 84.9 17.8
```

```
##
```

```
## See ?details_linear_reg_stan for details within parsnip
```

```
## * For help interpreting the printed output see ?print.stanreg
```

What was actually run?

```
linear_reg() %>%  
  set_engine(  
    "stan",  
    prior_intercept = rstanarm::student_t(df = 1),  
    prior = rstanarm::student_t(df = 1),  
    seed = 1234  
  ) %>%  
  translate()
```

```
## Linear Regression Model Specification (regression)  
##  
## Engine-Specific Arguments:  
##   prior_intercept = rstanarm::student_t(df = 1)  
##   prior = rstanarm::student_t(df = 1)  
##   seed = 1234  
##  
## Computational engine: stan  
##  
## Model fit template:  
## rstanarm::stan_glm(formula = missing_arg(), data = missing_arg(),  
##   weights = missing_arg(), prior_intercept = rstanarm::student_t(df = 1),  
##   prior = rstanarm::student_t(df = 1), seed = 1234, family = stats::gaussian,  
##   refresh = 0)
```

Back to broom

```
broom::tidy(bayes_tm)
```

```
## Error in warn_on_stanreg(x): The supplied model object seems to be outputted from the rstanarm package. Tidy
```

```
broom.mixed::tidy(bayes_tm)
```

```
## # A tibble: 4 × 3
##   term                estimate std.error
##   <chr>                <dbl>    <dbl>
## 1 (Intercept)          98.2      58.8
## 2 volume                0.829    0.0733
## 3 coverpaperback      -0.285    3.53
## 4 volume:coverpaperback -0.197    0.0510
```

```
broom.mixed::glance(bayes_tm)
```

```
## # A tibble: 1 × 4
##   algorithm    pss  nobs sigma
##   <chr>      <dbl> <int> <dbl>
## 1 sampling  4000    15  84.9
```

Augment

```
augment(bayes_tm, new_data=books)
```

```
## # A tibble: 15 × 5
##   volume weight cover   .pred .resid
##   <dbl> <dbl> <fct>   <dbl> <dbl>
## 1   885   800 hardback  829.  -29.2
## 2  1016   950 hardback  938.   12.3
## 3  1125  1050 hardback 1028.   22.1
## 4   239   350 hardback  294.   55.5
## 5   701   750 hardback  677.   73.1
## 6   641   600 hardback  627.  -27.3
## 7  1228  1075 hardback 1113.  -38.2
## 8   412   250 paperback 355. -105.
## 9   953   700 paperback 696.    4.16
## 10  929   650 paperback 681.  -30.7
## 11 1492   975 paperback 1036. -60.8
## 12  419   350 paperback 359.  -9.05
## 13 1010   950 paperback 732.  218.
## 14  595   425 paperback 470.  -45.1
## 15 1034   725 paperback 747.  -21.9
```

Predictions

```
bayes_tm %>%  
  augment(  
    new_data = tidyr::expand_grid(  
      volume = seq(0, 1500, by=5),  
      cover = c("hardback", "paperback") %>% as.factor()  
    )  
  ) %>%  
  rename(weight = .pred) %>%  
  ggplot(aes(x = volume, y = weight, color = cover, group = cover)) +  
    geom_line() +  
    geom_point(data = books)
```


Cross validation and Feature engineering

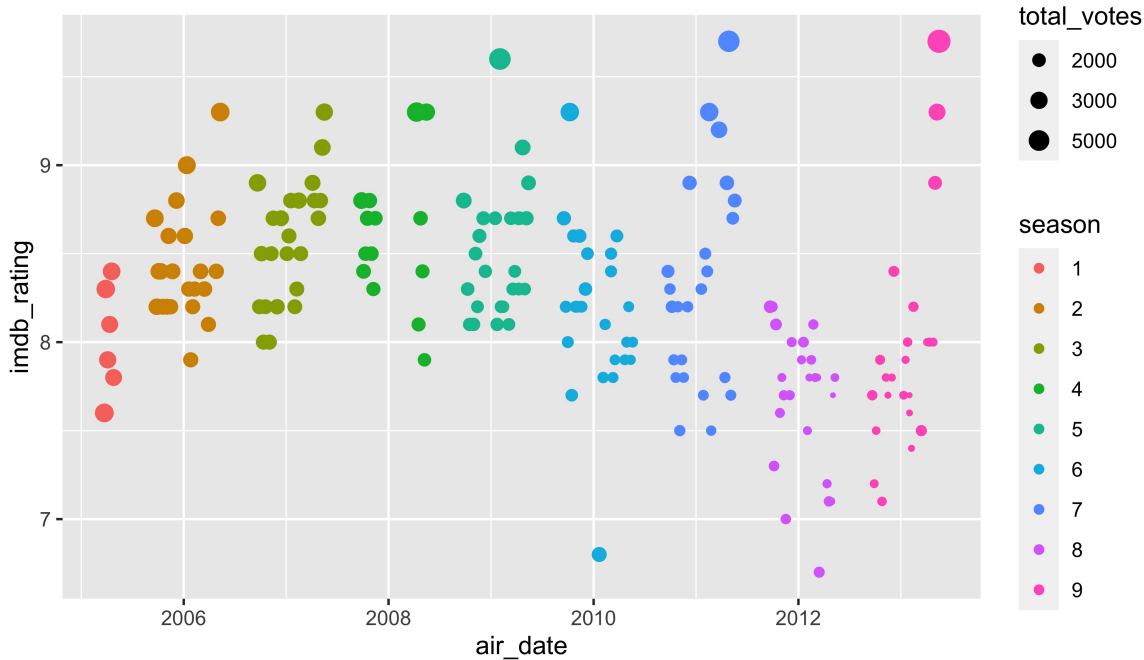
The Office & IMDB

```
(office_ratings = read_csv("data/office_ratings.csv"))
```

```
## # A tibble: 188 × 6
##   season episode title      imdb_rating total_votes air_date
##   <dbl>   <dbl> <chr>          <dbl>         <dbl> <date>
## 1     1     1     1 Pilot           7.6           3706 2005-03-24
## 2     2     1     2 Divers...       8.3           3566 2005-03-29
## 3     3     1     3 Health...       7.9           2983 2005-04-05
## 4     4     1     4 The Al...       8.1           2886 2005-04-12
## 5     5     1     5 Basket...       8.4           3179 2005-04-19
## 6     6     1     6 Hot Gi...       7.8           2852 2005-04-26
## 7     7     2     1 The Du...       8.7           3213 2005-09-20
## 8     8     2     2 Sexual...       8.2           2736 2005-09-27
## 9     9     2     3 Office...       8.4           2742 2005-10-04
## 10    10     2     4 The Fi...       8.4           2713 2005-10-11
## # ... with 178 more rows
```

These data are from data.world, by way of TidyTuesday.

Rating vs Air Date



Test-train split



```
set.seed(123)
(office_split = initial_split(office_ratings, pro
```

```
## <Analysis/Assess/Total>
## <150/38/188>
```

```
(office_train = training(office_split))
```

```
## # A tibble: 150 × 6
##   season episode title      imdb_rating total_vot
##   <dbl>   <dbl> <chr>          <dbl>      <dbl>
## 1     8     18 Last D...         7.8         14
## 2     9     14 Vandal...         7.6         14
## 3     2      8 Perfor...         8.2         24
## 4     9      5 Here C...         7.1         15
## 5     3     22 Beach ...         9.1         27
## 6     7      1 Nepoti...         8.4         18
## 7     3     15 Phylli...         8.3         22
## 8     9     21 Livin'...         8.9         20
## 9     9      9 Promos           8           14
```

```
(office_test = testing(office_split))
```

```
## # A tibble: 38 × 6
##   season episode title      imdb_rating total_votes ai
##   <dbl>   <dbl> <chr>          <dbl>      <dbl> <dbl>
## 1     1      2 Divers...         8.3       3566 20
## 2     2      4 The Fi...         8.4       2713 20
## 3     2      9 E-Mail...         8.4       2527 20
## 4     2     12 The In...          9         3282 20
## 5     2     22 Casino...         9.3       3644 20
## 6     3      5 Initia...         8.2       2254 20
## 7     3     16 Busine...         8.8       2622 20
## 8     3     17 Cockta...         8.5       2264 20
## 9     4      6 Branch...         8.5       2185 20
```

Feature engineering with dplyr

```
office_train %>%
  mutate(
    season = as_factor(season),
    month = lubridate::month(air_date),
    wday = lubridate::wday(air_date),
    top10_votes = as.integer(total_votes > quantile(total_votes, 0.9))
  )
```

```
## # A tibble: 150 × 9
##   season episode title          imdb_rating total_votes air_date   month  wday top10_votes
##   <fct>   <dbl> <chr>          <dbl>         <dbl> <date>   <dbl> <dbl> <int>
## 1 8         18 Last Day in Florida      7.8         1429 2012-03-08     3     5     0
## 2 9         14 Vandalism                7.6         1402 2013-01-31     1     5     0
## 3 2          8 Performance Review      8.2         2416 2005-11-15    11     3     0
## 4 9          5 Here Comes Treble       7.1         1515 2012-10-25    10     5     0
## 5 3         22 Beach Games            9.1         2783 2007-05-10     5     5     0
## 6 7          1 Nepotism                8.4         1897 2010-09-23     9     5     0
## 7 3         15 Phyllis' Wedding      8.3         2283 2007-02-08     2     5     0
## 8 9         21 Livin' the Dream      8.9         2041 2013-05-02     5     5     0
## 9 9         18 Promos                 8           1445 2013-04-04     4     5     0
## 10 8         12 Pool Party            8           1612 2012-01-19     1     5     0
## # ... with 140 more rows
```

Better living through recipes



```
(r = recipe(imdb_rating ~ ., data = office_train)
```

```
## Recipe
##
## Inputs:
##
##      role #variables
##  outcome      1
##  predictor     5
```

```
summary(r)
```

```
## # A tibble: 6 × 4
##   variable  type    role    source
##   <chr>     <chr>  <chr>   <chr>
## 1 season    numeric predictor original
## 2 episode   numeric predictor original
## 3 title     nominal predictor original
## 4 total_votes numeric predictor original
## 5 air_date  date    predictor original
## 6 imdb_rating numeric outcome  original
```

Recipe roles

```
(r = recipe(imdb_rating ~ ., data = office_train)
  update_role(title, new_role = "ID")
)
```

```
## Recipe
##
## Inputs:
##
##      role #variables
##      ID      1
##      outcome  1
##      predictor 4
```

```
summary(r)
```

```
## # A tibble: 6 × 4
##   variable   type    role    source
##   <chr>     <chr>  <chr>  <chr>
## 1 season    numeric predictor original
## 2 episode    numeric predictor original
## 3 title      nominal ID      original
## 4 total_votes numeric predictor original
## 5 air_date   date    predictor original
## 6 imdb_rating numeric outcome  original
```

Adding features (month & day of week)

```
(r = recipe(imdb_rating ~ ., data = office_train)
  update_role(title, new_role = "ID") %>%
  step_date(air_date, features = c("dow", "month"
)
```

```
## Recipe
##
## Inputs:
##
##   role #variables
##   ID      1
##   outcome 1
##   predictor 4
##
## Operations:
##
## Date features from air_date
```

```
summary(r)
```

```
## # A tibble: 6 × 4
##   variable    type    role    source
##   <chr>      <chr>  <chr>  <chr>
## 1 season      numeric predictor original
## 2 episode      numeric predictor original
## 3 title        nominal ID      original
## 4 total_votes  numeric predictor original
## 5 air_date     date    predictor original
## 6 imdb_rating  numeric outcome  original
```


Adding Holidays

```
(r = recipe(imdb_rating ~ ., data = office_train) %>%  
  update_role(title, new_role = "ID") %>%  
  step_date(air_date, features = c("dow", "month")) %>%  
  step_holiday(  
    air_date,  
    holidays = c("USThanksgivingDay", "USChristmasDay", "USNewYearsDay", "USIndependenceDay"),  
    keep_original_cols = FALSE  
  )  
)
```

```
## Recipe
```

```
##
```

```
## Inputs:
```

```
##
```

```
##      role #variables
```

```
##      ID      1
```

```
##      outcome  1
```

```
##      predictor  4
```

```
##
```

```
## Operations:
```

```
##
```

```
## Date features from air_date
```

```
## Holiday features from air_date
```

Seasons as factors

```
(r = recipe(imdb_rating ~ ., data = office_train) %>%  
  update_role(title, new_role = "ID") %>%  
  step_date(air_date, features = c("dow", "month")) %>%  
  step_holiday(  
    air_date,  
    holidays = c("USThanksgivingDay", "USChristmasDay", "USNewYearsDay", "USIndependenceDay"),  
    keep_original_cols = FALSE  
  ) %>%  
  step_num2factor(season, levels = as.character(1:9))  
)
```

```
## Recipe
```

```
##
```

```
## Inputs:
```

```
##
```

```
##      role #variables
```

```
##      ID      1
```

```
##      outcome  1
```

```
##      predictor  4
```

```
##
```

```
## Operations:
```

```
##
```

```
## Date features from air_date
```

```
## Holiday features from air_date
```

Dummy coding

```
(r = recipe(imdb_rating ~ ., data = office_train) %>%
  update_role(title, new_role = "ID") %>%
  step_date(air_date, features = c("dow", "month")) %>%
  step_holiday(
    air_date,
    holidays = c("USThanksgivingDay", "USChristmasDay", "USNewYearsDay", "USIndependenceDay"),
    keep_original_cols = FALSE
  ) %>%
  step_num2factor(season, levels = as.character(1:9)) %>%
  step_dummy(all_nominal_predictors())
)
```

```
## Recipe
```

```
##
```

```
## Inputs:
```

```
##
```

```
##      role #variables
```

```
##      ID      1
```

```
## outcome      1
```

```
## predictor     4
```

```
##
```

```
## Operations:
```

```
##
```

```
## Date features from air_date
```

Why no `top10_votes`?

There does not appear to be a `step_*()` function that implements the quantile calculation necessary for the `top10_votes` feature above, custom recipe steps can be created see [this](#) for an relevant example.

Preparing a recipe

```
prep(r)
```

```
## Recipe
##
## Inputs:
##
##      role #variables
##      ID      1
## outcome      1
## predictor      4
##
## Training data contained 150 data points and no missing data.
##
## Operations:
##
## Date features from air_date [trained]
## Holiday features from air_date [trained]
## Factor variables from season [trained]
## Dummy variables from season, air_date_dow, air_date_month [trained]
```

Baking a recipe

```
prep(r) %>%  
  bake(new_data = office_train)
```

```
## # A tibble: 150 × 33  
##   episode title      total_votes imdb_rating air_date_USThanksg... air_date_USChris... air_date_USNewYe...  
##   <dbl> <fct>          <dbl>         <dbl>          <dbl>          <dbl>          <dbl>  
## 1     18 Last Day...     1429          7.8            0              0              0  
## 2     14 Vandalism     1402          7.6            0              0              0  
## 3      8 Performa...    2416          8.2            0              0              0  
## 4      5 Here Com...    1515          7.1            0              0              0  
## 5     22 Beach Ga...    2783          9.1            0              0              0  
## 6      1 Nepotism     1897          8.4            0              0              0  
## 7     15 Phyllis'...    2283          8.3            0              0              0  
## 8     21 Livin' t...    2041          8.9            0              0              0  
## 9     18 Promos      1445          8              0              0              0  
## 10    12 Pool Par...    1612          8              0              0              0  
## # ... with 140 more rows, and 26 more variables: air_date_USIndependenceDay <dbl>, season_X2 <dbl>,  
## #   season_X3 <dbl>, season_X4 <dbl>, season_X5 <dbl>, season_X6 <dbl>, season_X7 <dbl>,  
## #   season_X8 <dbl>, season_X9 <dbl>, air_date_dow_Mon <dbl>, air_date_dow_Tue <dbl>,  
## #   air_date_dow_Wed <dbl>, air_date_dow_Thu <dbl>, air_date_dow_Fri <dbl>, air_date_dow_Sat <dbl>,  
## #   air_date_month_Feb <dbl>, air_date_month_Mar <dbl>, air_date_month_Apr <dbl>,  
## #   air_date_month_May <dbl>, air_date_month_Jun <dbl>, air_date_month_Jul <dbl>,  
## #   air_date_month_Aug <dbl>, air_date_month_Sep <dbl>, air_date_month_Oct <dbl>, ...
```

Informative features?

```
prep(r) %>%  
  bake(new_data = office_train) %>%  
  map_int(~ length(unique(.x)))
```

```
##           episode           title           total_votes  
##           26             150             142  
##      imdb_rating air_date_USThanksgivingDay air_date_USChristmasDay  
##           26             1             1  
## air_date_USNewYearsDay air_date_USIndependenceDay           season_X2  
##           1             1             2  
##           season_X3           season_X4           season_X5  
##           2             2             2  
##           season_X6           season_X7           season_X8  
##           2             2             2  
##           season_X9           air_date_dow_Mon           air_date_dow_Tue  
##           2             1             2  
##           air_date_dow_Wed           air_date_dow_Thu           air_date_dow_Fri  
##           1             2             1  
##           air_date_dow_Sat           air_date_month_Feb           air_date_month_Mar  
##           1             2             2  
##           air_date_month_Apr           air_date_month_May           air_date_month_Jun  
##           2             2             1  
##           air_date_month_Jul           air_date_month_Aug           air_date_month_Sep  
##           1             1             2
```

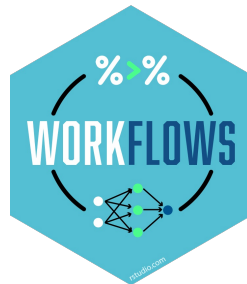
Removing zero variance predictors

```
r = recipe(imdb_rating ~ ., data = office_train) %>%
  update_role(title, new_role = "ID") %>%
  step_date(air_date, features = c("dow", "month")) %>%
  step_holiday(
    air_date,
    holidays = c("USThanksgivingDay", "USChristmasDay", "USNewYearsDay", "USIndependenceDay"),
    keep_original_cols = FALSE
  ) %>%
  step_num2factor(season, levels = as.character(1:9)) %>%
  step_dummy(all_nominal_predictors()) %>%
  step_zv(all_predictors())

prep(r) %>%
  bake(new_data = office_train)
```

```
## # A tibble: 150 × 22
##   episode title total_votes imdb_rating season_X2 season_X3 season_X4 season_X5 season_X6 season_X7
##   <dbl> <fct>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
## 1     18 Last...    1429        7.8         0         0         0         0         0         0
## 2     14 Vand...    1402        7.6         0         0         0         0         0         0
## 3     8 Perf...    2416        8.2         1         0         0         0         0         0
## 4     5 Here...    1515        7.1         0         0         0         0         0         0
## 5    22 Beac...    2783        9.1         0         1         0         0         0         0
## 6     1 Nepo...    1897        8.4         0         0         0         0         0         1
## 7    15 Phyl...    2283        8.3         0         1         0         0         0         0
## 8    21 Livi...    2041        8.9         0         0         0         0         0         0
## 9    18 Prom...    1445         8         0         0         0         0         0         0
## 10   12 Pool...    1612         8         0         0         0         0         0         0
## # ... with 140 more rows, and 12 more variables: season_X8 <dbl>, season_X9 <dbl>,
## #   air_date_dow_Tue <dbl>, air_date_dow_Thu <dbl>, air_date_month_Feb <dbl>,
```


Really putting it all together



```
(office_work = workflow() %>%  
  add_recipe(r) %>%  
  add_model(  
    linear_reg() %>%  
    set_engine("lm")  
  )  
)
```

```
## == Workflow ==  
## Preprocessor: Recipe  
## Model: linear_reg()  
##  
## — Preprocessor —  
## 5 Recipe Steps  
##  
## • step_date()  
## • step_holiday()  
## • step_num2factor()  
## • step_dummy()  
## • step_zv()  
##  
## — Model —  
## Linear Regression Model Specification (regressi
```

Workflow fit

```
(office_fit = office_work %>%  
  fit(data = office_train))
```

```
## == Workflow [trained] ==  
## Preprocessor: Recipe  
## Model: linear_reg()  
##  
## — Preprocessor —  
## 5 Recipe Steps  
##  
## • step_date()  
## • step_holiday()  
## • step_num2factor()  
## • step_dummy()  
## • step_zv()  
##  
## — Model —  
##  
## Call:  
## stats::lm(formula = ..y ~ ., data = data)  
##  
## Coefficients:  
##      (Intercept)      episode      total_votes      season_X2      season_X3  
##      6.2557856      -0.0081872      0.0003838      0.8389817      1.1277917  
##      season_X4      season_X5      season_X6      season_X7      season_X8  
##      1.1519446      1.1767757      1.0899544      1.0671645      0.5024513  
##      season_X9      air_date_dow_Tue      air_date_dow_Thu      air_date_month_Feb      air_date_month_Mar  
##      0.6981099      0.4945405      0.3699592      -0.0089843      -0.0194673  
##      air_date_month_Apr      air_date_month_May      air_date_month_Sep      air_date_month_Oct      air_date_month_Nov  
##      0.0895888      0.2105803      -0.0776988      -0.2059183      -0.1895729
```

Performance

```
office_fit %>%  
  augment(office_train) %>%  
  rmse(imdb_rating, .pred)
```

```
## # A tibble: 1 × 3  
##   .metric .estimator .estimate  
##   <chr>   <chr>         <dbl>  
## 1 rmse    standard         0.305
```

```
office_fit %>%  
  augment(office_test) %>%  
  rmse(imdb_rating, .pred)
```

```
## # A tibble: 1 × 3  
##   .metric .estimator .estimate  
##   <chr>   <chr>         <dbl>  
## 1 rmse    standard         0.423
```

k-fold cross validation

	training				testing
fold 1	validate	train	train	train	train
fold 2	train	validate	train	train	train
fold 3	train	train	validate	train	train
fold 4	train	train	train	validate	train
fold 5	train	train	train	train	validate

Creating folds

```
set.seed(123)
(folds = vfold_cv(office_train, v=5))
```

```
## # 5-fold cross-validation
## # A tibble: 5 × 2
##   splits          id
##   <list>         <chr>
## 1 <split [120/30]> Fold1
## 2 <split [120/30]> Fold2
## 3 <split [120/30]> Fold3
## 4 <split [120/30]> Fold4
## 5 <split [120/30]> Fold5
```

```
(office_fit_folds = office_work %>%
  fit_resamples(folds)
)
```

```
## ! Fold2: preprocessor 1/1, model 1/1 (predictions): prediction from a rank-deficient fit may be misle...
## Warning: This tuning result has notes. Example notes on model fitting include:
## preprocessor 1/1, model 1/1 (predictions): prediction from a rank-deficient fit may be misleading
## # Resampling results
## # 5-fold cross-validation
```

Fold performance

```
tune::collect_metrics(office_fit_folds)
```

```
## # A tibble: 2 × 6
##   .metric .estimator  mean      n std_err .config
##   <chr>   <chr>      <dbl> <int>  <dbl> <chr>
## 1 rmse    standard    0.421     5  0.0511 Preprocessor1_Model1
## 2 rsq     standard    0.550     5  0.0663 Preprocessor1_Model1
```

```
tune::collect_metrics(office_fit_folds, summarize = FALSE) %>%
  filter(.metric == "rmse")
```

```
## # A tibble: 5 × 5
##   id    .metric .estimator .estimate .config
##   <chr> <chr>   <chr>      <dbl> <chr>
## 1 Fold1 rmse    standard    0.618 Preprocessor1_Model1
## 2 Fold2 rmse    standard    0.382 Preprocessor1_Model1
## 3 Fold3 rmse    standard    0.321 Preprocessor1_Model1
## 4 Fold4 rmse    standard    0.410 Preprocessor1_Model1
## 5 Fold5 rmse    standard    0.377 Preprocessor1_Model1
```

More on the `tune` package next time