Recruiting Challenge

Performance of the S&P500 in 2019

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Data Wrangling

Data Retrieval and Cleanup

The first goal is to retrieve the list of companies that are currently listed in the S&P500 and their corresponding GICS sectors. We also retrieve the latest information for these stocks – such as market capitalization – from the different stock exchanges.

```
sp500_companies <- tq_index("SP500") %>%
    left_join(bind_rows(tq_exchange("AMEX"),
                        tq_exchange("NASDAQ"),
                        tq_exchange("NYSE")),
              by = "symbol") %>%
    distinct() %>%
    select(symbol, company = company.x, weight, sector = sector.x,
           shares_held, market_cap = market.cap, industry)

sp500_companies %>% glimpse()
```

```
## Observations: 505
## Variables: 7
## $ symbol      <chr> "AAPL", "MSFT", "AMZN", "FB", "BRK.B", "GOOGL", "GOOG",...
## $ company     <chr> "Apple Inc.", "Microsoft Corporation", "Amazon.com Inc....
## $ weight      <dbl> 0.047931162, 0.045515896, 0.029004745, 0.019405346, 0.0...
## $ sector      <chr> "Information Technology", "Information Technology", "Co...
## $ shares_held <dbl> 48669720, 88896700, 4853403, 28042064, 22793356, 349117...
## $ market_cap  <chr> "$1389.56B", "$1245.63B", "$937.7B", "$632.83B", NA, "$...
## $ industry    <chr> "Computer Manufacturing", "Computer Software: Prepackag...
```

Now that we have data for all 505 stocks in the exchange, their weights, and their market capitalization, we query the Yahoo Finance API for historical trading data. We only need data with monthly resolution from 2018-12-31 to 2019-12-31.

```
sp500_raw <- sp500_companies %>%
    pull(symbol) %>%
    map_chr(~ str_replace(.x,"\\.","-")) %>%  ## cleanup tickers for API call
    tidyquant::tq_get(from = "2018-12-31",  ## defaults to Yahoo Finance API
                      to = "2020-01-01") %>%
    mutate(symbol = map_chr(symbol, ~ str_replace(.x, "-", "\\."))) ## cleanup

sp500_raw %>% glimpse()
```

```
## Observations: 127,468
## Variables: 8
## $ symbol   <chr> "AAPL", "AAPL", "AAPL", "AAPL", "AAPL", "AAPL", "AAPL", "A...
## $ date     <date> 2018-12-31, 2019-01-02, 2019-01-03, 2019-01-04, 2019-01-0...
## $ open     <dbl> 158.53, 154.89, 143.98, 144.53, 148.70, 149.56, 151.29, 15...
## $ high     <dbl> 159.36, 158.85, 145.72, 148.55, 148.83, 151.82, 154.53, 15...
## $ low      <dbl> 156.48, 154.23, 142.00, 143.80, 145.90, 148.52, 149.63, 15...
## $ close    <dbl> 157.74, 157.92, 142.19, 148.26, 147.93, 150.75, 153.31, 15...
## $ volume   <dbl> 35003500, 37039700, 91312200, 58607100, 54777800, 41025300...
## $ adjusted <dbl> 155.4050, 155.5824, 140.0852, 146.0654, 145.7403, 148.5185...
```

The raw data contains the usual trading information. We will focus on the adjusted close values (which include dividends, splits, etc). Now we perform a preprocessing step to make computations on the performance of assets more straightforward.

```
start <- sp500_raw %>% filter(date == "2018-12-31")
end <- sp500_raw %>% filter(date == "2019-12-31")

sp500_processed <- start %>%
    full_join(end,
              by = "symbol",
              suffix = c("_2018", "_2019")) %>%
    left_join(sp500_companies, by = "symbol") %>%
    mutate(return = (adjusted_2019 - adjusted_2018) * 100 / adjusted_2018)

sp500_processed
```

```
## # A tibble: 505 x 22
##    symbol date_2018  open_2018 high_2018 low_2018 close_2018 volume_2018
##    <chr>  <date>         <dbl>     <dbl>    <dbl>      <dbl>       <dbl>
##  1 AAPL   2018-12-31     159.      159.     156.       158.     35003500
##  2 MSFT   2018-12-31     101.      102.     100.       102.     33173800
##  3 AMZN   2018-12-31    1511.     1521.    1487       1502.      6954500
##  4 FB     2018-12-31     134.      135.     130.       131.     24625300
##  5 BRK.B  2018-12-31     204.      205.     201        204.      5451900
##  6 GOOGL  2018-12-31    1058.     1063.    1033.      1045.      1655500
##  7 GOOG   2018-12-31    1051.     1053.    1024.      1036.      1493300
##  8 JPM    2018-12-31      97.6      98.8     96.8       97.6    13237200
##  9 JNJ    2018-12-31     128.      130.     127.       129.      7409900
## 10 V      2018-12-31     132.      132.     130.       132.      7976000
## # ... with 495 more rows, and 15 more variables: adjusted_2018 <dbl>,
## #   date_2019 <date>, open_2019 <dbl>, high_2019 <dbl>, low_2019 <dbl>,
## #   close_2019 <dbl>, volume_2019 <dbl>, adjusted_2019 <dbl>, company <chr>,
## #   weight <dbl>, sector <chr>, shares_held <dbl>, market_cap <chr>,
## #   industry <chr>, return <dbl>
```

Further computations on the 2019 performance are straightforward as the return is already computed for all 505 stocks in the S&P500.

Sector Performance

Calculating the weighted mean is straightforward after our preprocessing step. We are computing, for each sector, the average weighted by the market capitalization of the companies.

```
sector_performance <- sp500_processed %>%
    mutate(market_cap = map_dbl(market_cap, parse_human_readable_number)) %>%
    group_by(sector) %>%
    summarize(wt_avg_return = weighted_mean(return, market_cap, na.rm=T)) %>%
    arrange(desc(wt_avg_return))

sector_performance
```

```
## # A tibble: 11 x 2
##    sector                 wt_avg_return
##    <chr>                          <dbl>
##  1 Information Technology          55.7
##  2 Financials                      37.2
##  3 Communication Services          34.2
##  4 Industrials                     32.7
##  5 Real Estate                     32.7
##  6 Materials                       31.1
##  7 Consumer Discretionary          30.4
##  8 Consumer Staples                29.8
##  9 Utilities                       29.8
## 10 Health Care                     22.5
## 11 Energy                          12.9
```

The result shows the weight average return for the eleven sectors ranked in descending order.

Relative Annual Returns

To find the relative annual return for each of the 505 stocks, we join the previous computation of returns in our processed data with the sector performance, and perform the simple vectorized computation.

```
rel_annual_returns <- sp500_processed %>%
    left_join(sector_performance, by = "sector") %>%
    mutate(rel_return = return / wt_avg_return) %>%
    select(symbol, sector, rel_return) %>%
    arrange(desc(rel_return))

rel_annual_returns
```

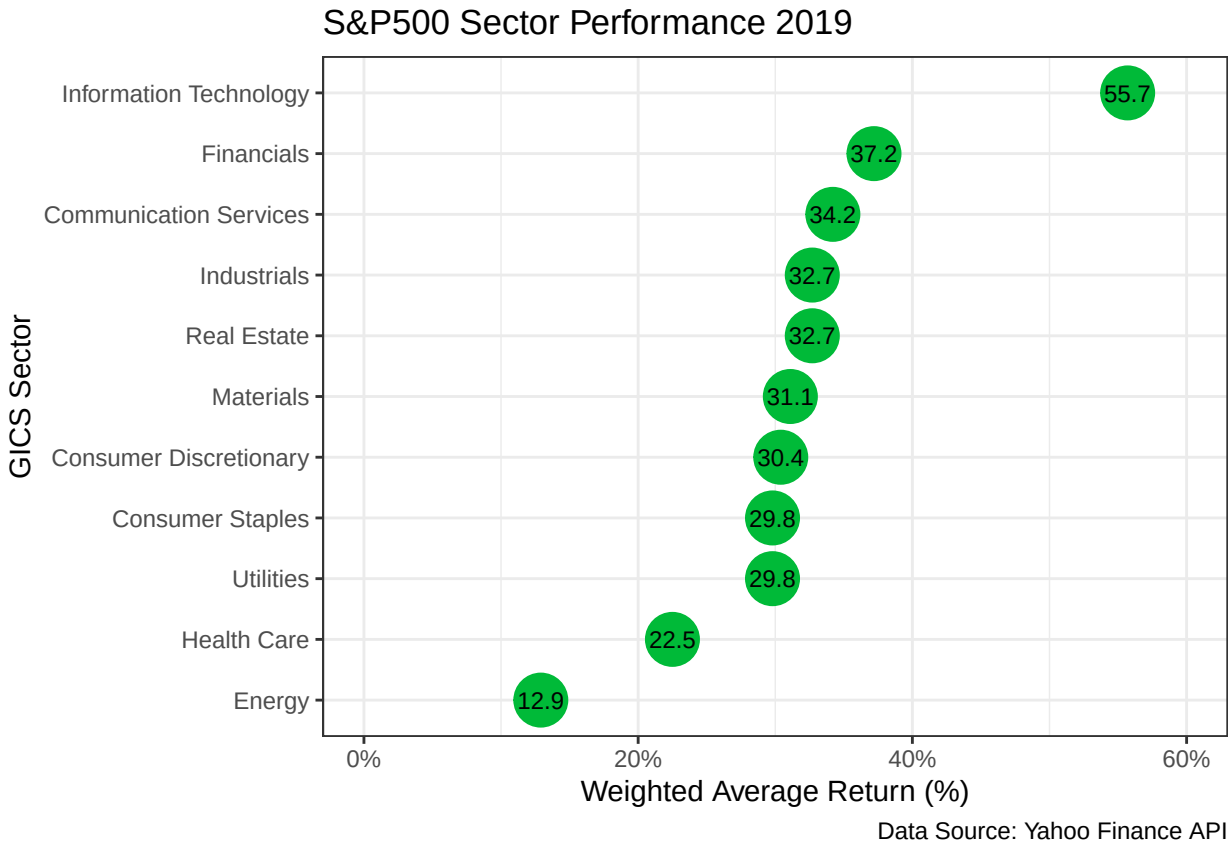
```
## # A tibble: 505 x 3
##    symbol sector                 rel_return
##    <chr>  <chr>                       <dbl>
##  1 HES    Energy                       5.25
##  2 OKE    Energy                       3.70
##  3 KMI    Energy                       3.44
##  4 TGT    Consumer Discretionary       3.30
##  5 CMG    Consumer Discretionary       3.09
##  6 CPRT   Industrials                  2.76
##  7 NBL    Energy                       2.74
```

```
##  8 AMD    Information Technology       2.66
##  9 COTY   Consumer Staples             2.65
## 10 PSX    Energy                       2.63
## # ... with 495 more rows
```

The table above contains the ratio of annual return over respective sector performance for 2019 for all 505 stocks.

Results

Sector Performance in 2019



Relative Annual Returns in 2019