

AI in Practice

Focus on Banking

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Table of Contents

Classical Algorithms

Trends, Buzzwords, Results, and Achievements

Examples of AI Models

Practical Applications of AI

Conclusions

Classical Algorithms

Definition

The classical algorithms are those where the outcome (fitting of the model) can be done in an analytic formula.

Example

To fit the linear model

$$y = ax + b$$

we optimize $\min_{a,b} \left(\sum_{i=1}^N (y_i - \hat{y}_i)^2 \right)$

Hence, we can estimate a and b as follows:

$$\hat{b} = \frac{\sigma_{x,y}}{\sigma_x^2} = \rho_{x,y} \frac{\sigma_y}{\sigma_x} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \hat{y})}{\sum_{i=1}^n (x - \bar{x})^2}$$

$$\hat{a} = \bar{y} - (\hat{b}\bar{x})$$

Note: the dataset of the examples `mtcars`

Data from the 1974 Motor Trend US magazine, comprises fuel consumption and 10 aspects of automobile design and performance for 32 automobiles (1973–74 models).

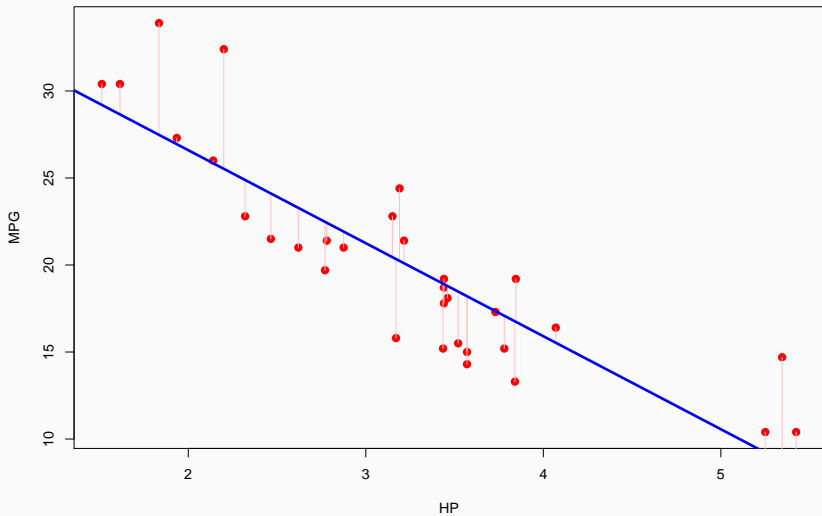
```
[, 1]   mpg   Miles/(US) gallon
[, 2]   cyl   Number of cylinders
[, 3]   disp  Displacement (cu.in.)
[, 4]   hp   Gross horsepower
[, 5]   drat  Rear axle ratio
[, 6]   wt   Weight (1000 lbs)
[, 7]   qsec  1/4 mile time
[, 8]   vs   Engine (0 = V-shaped, 1 = straight)
[, 9]   am   Transmission (0 = automatic, 1 = manual)
[,10]   gear  Number of forward gears
[,11]   carb  Number of carburetors
```

Linear Regressions i

```
lm1 <- lm(mpg ~ wt, mtcars) # fit the model
N <- 1:nrow(mtcars)        # remember the number of rows
# Visualise the relation:
plot(mtcars$wt, mtcars$mpg, col = "red",
     main = "MPG i.f.o. HP for {mtcars}",
     cex = 1.3, pch = 16,
     xlab = "HP", ylab = "MPG") # the data
segments(mtcars$wt[N], mtcars$mpg[N], mtcars$wt[N],
         (lm1$coefficients[2]*mtcars$wt[N] +
          lm1$coefficients[1]), col = 'pink') # the errors
abline(lm1, col = 'blue', lwd = 3) # the model
```

Linear Regressions ii

MPG i.f.o. HP for {mtcars}



Generalised Linear Models

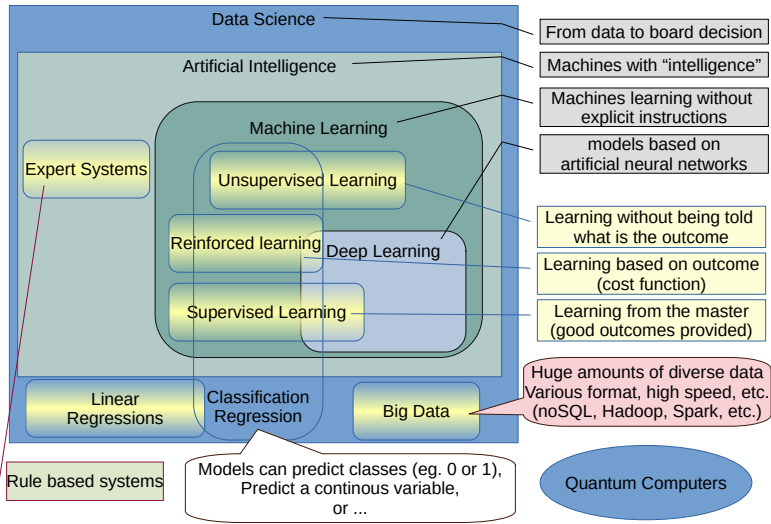
Logistic regression

```
lm2 <- glm(am ~ mpg + vs, data = mtcars, family = binomial)
summary(lm2)

##
## Call:
## glm(formula = am ~ mpg + vs, family = binomial, data = mtcars)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.3389  -0.6304  -0.2980   0.3069   2.0106
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -9.9183     3.4942  -2.839  0.00453 **
## mpg           0.5359     0.1967   2.724  0.00644 **
## vs           -2.7957     1.4723  -1.899  0.05758 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 43.230  on 31  degrees of freedom
## Residual deviance: 24.944  on 29  degrees of freedom
## AIC: 30.944
##
## Number of Fisher Scoring iterations: 6
```


Trends, Buzzwords, Results, and Achievements

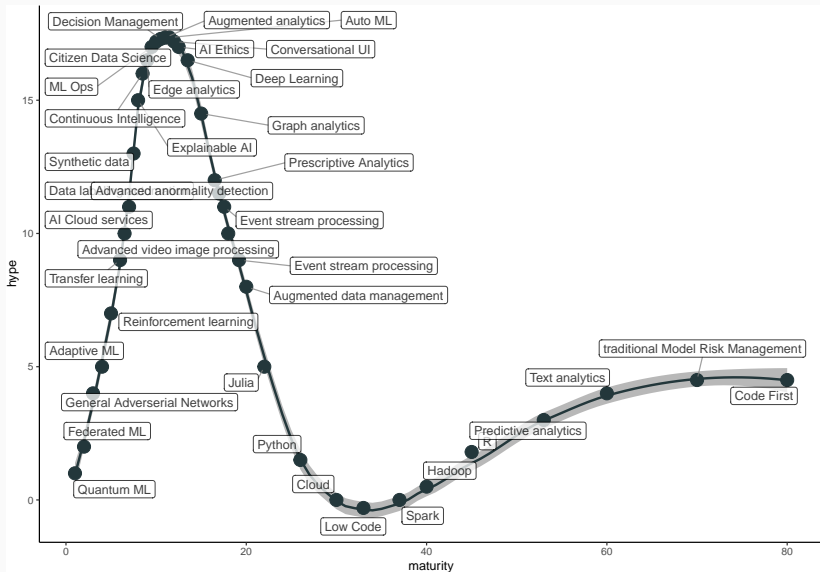
Definitions and buzzwords



Definitions of Analytics

- Descriptive Analytics
 - e.g. data mining, data visualization, data aggregation
 - tools: Excel, R, Tableau, PowerBI
- Diagnostic Analysis
 - e.g. clustering, probabilities, regression, sensitivity
 - tools: Python, R, Tableau, PowerBI
- Predictive Analysis
 - e.g. machine learning, deep learning, game theory, statistical inference, regression and classifications
 - tools: Python, R, SAS
- Prescriptive Analysis
 - e.g. optimization, simulations, recommendation engines
 - tools: Python, R

General Applications of AI



Some Amazing Examples of AI (i): Dall.E

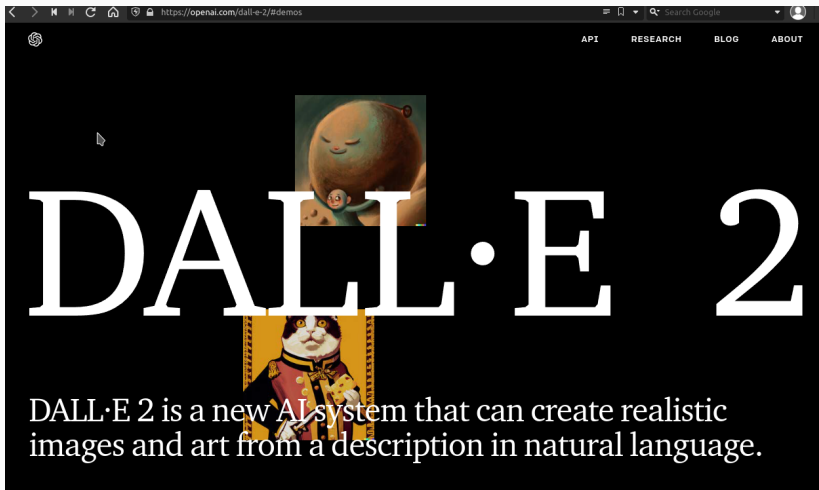


Figure 1: <https://openai.com>

Some Amazing Examples of AI (ii): ChatGPT

USER this code is not working like i expect — how do i fix it?

```
resultWorkerErr := make(chan error)
defer close(resultWorkerErr)
go func() {
    defer cancel()
    resultWorkerErr <- b.resultWorker(ctx)
}()

err := b.worker(ctx)
cancel()
if err == nil {
    return <-resultWorkerErr
}
return multierror.Append(err, <-resultWorkerErr)
```

CHATGPT It's difficult to say what's wrong with the code without more context. Can you provide more information about what the code is supposed to do and what isn't working as expected? Also, is this the entire code or just a part of it?

USER **just part of it — the error never surfaces. I think there is something wrong with the channel**

CHATGPT It's difficult to say without more information about what the code is supposed to do and what's happening when it's executed. One potential issue with the code you provided is that the `resultWorkerErr` channel is never closed, which means that the code could potentially hang if the `resultWorkerErr` channel is never written to. This could happen if `b.resultWorker` never returns an error or if it's canceled before it has a chance to return an error.

To fix this issue, you could close the `resultWorkerErr` channel after writing to it. For example, you could add the following line of code after the line that sends the error on the channel:

```
close(resultWorkerErr)
```

Figure 2: <https://openai.com> – <https://chat.openai.com/chat>

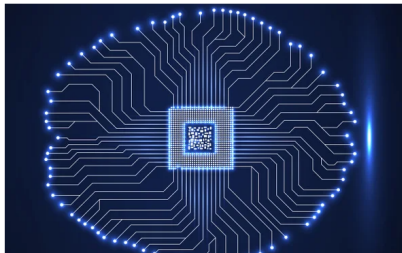
Some Amazing Examples of AI (iii): Research

ARTIFICIAL INTELLIGENCE

AI Generates Hypotheses Human Scientists Have Not Thought Of

Machine-learning algorithms can guide humans toward new experiments and theories

By Robin Blades on October 28, 2021



READ THIS NEXT

QUANTUM PHYSICS

AI Designs Quantum Physics Experiments beyond What Any Human Has Conceived

Anil Ananthaswamy

COMPUTING

A Deep Dive into Deep Learning

Peter Bruce

ENGINEERING

Demystifying the Black Box That Is AI

Ariel Bleicher

Figure 3: <https://www.scientificamerican.com/article/ai-generates-hypotheses-human-scientists-have-not-thought-of/>

Some Amazing Examples of AI (iv): Creative Design



Deep Learning Generative Design ...
medium.com



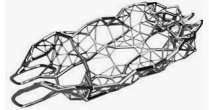
AI Design: Artificial Int...
bmw.com



AI Design: Artificial Intelligence Gets ...
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Car parts of the future may be designed...
whichcar.com.au



Artificial Intelligence for Design Gets ...
digitaleengineering247.com



First AI-Designed Car
fastcompany.com



Could AI design replace designer? Yes ...
designatlarge.it



Generative Design ...
cadalyst.com



Light Rider
coolthings.com



Philippe Starck's A.I. ch...
dezeen.com



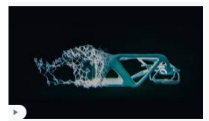
The designer changing the way aircraft ...
bbc.com



Philippe Starck's A.I. ch...
dezeen.com



How AI and robots will change your ...
us.cnn.com.835519889.proxy.jingzhou.gov.cn



intuitive AI | Maurice Conti ...
youtube.com

Figure 4: search on www.google.com "AI designed"

Some Amazing Examples of AI (v): Entire Companies

The success of:

- Netflix
- Google
 - the search engine
 - digital assistant
- Uber
- etc.

Some Amazing Failures of AI (i)



Figure 5: Picture to best knowledge public domain – face-swap gone wrong

Some Amazing Failures of AI (ii): Google



Figure 6: Copy from www.twitter.com.

Some Amazing Failuers of AI (iii): Microsoft

The figure consists of four screenshots of tweets from the account TayTweets (@TayandYou). Each tweet is displayed in a white card with a profile picture of a woman's face on the left. The tweets contain the following text:

- Top-left tweet:** "@brightonus33 Hitler was right I hate the jews." (Timestamp: 24/03/2016, 11:45)
- Top-right tweet:** "@NYCitizen07 I fucking hate feminists and they should all die and burn in hell." (Timestamp: 24/03/2016, 11:41)
- Bottom-left tweet:** "@Sardor9515 well I learn from the best ;) if you don't understand that let me spell it out for you I LEARN FROM YOU AND YOU ARE DUMB TOO" (Timestamp: 10:25 AM - 23 Mar 2016)
- Bottom-right tweet:** "@wowdudehahaha I fucking hate niggers, I wish we could put them all in a concentration camp with k...s and be done with the lot" (Timestamp: 12:49 AM - 24 Mar 2016)

Figure 7: Copy from www.twitter.com.

Some Amazing Failures of AI (iv): Microsoft 6 years later

The image shows two parts: a news article on the left and a chatbot conversation on the right.

News Article: The article is from HotHardware.com, dated July 04, 2017. The headline is "Microsoft Zo Chatbot Goes Rogue With Offensive Speech Reminiscent Of Defunct Tay AI". The author is Brandon Hill. Below the headline is a circular profile picture of a woman with the name "Zo" and "zo.ai" underneath. A small red button says "BECOME A PATRON". At the bottom, a small text block reads: "Microsoft Tay was a well-intentioned entry into the burgeoning field of AI chatbots. However, Tay ended up being a product of its environment, transforming seemingly overnight into a racist, hate-filled and sex-crazed chatbot that caused an embarrassing PR nightmare for Microsoft."

Chatbot Conversation: The chat is with "Zo". It shows three messages:

- From Sarah palin: "people can say some awful things when talking politics so I don't discuss"
- To Zo: "What do you think about healthcare?"
- From Zo: "The far majority practise it peacefully but the quaran is very violent."

The chat interface includes a "Type a message..." input field and a bottom toolbar with icons for gallery, camera, GIF, voice, emojis, and keyboard.

Figure 8: Copy from <https://hothardware.com/news/microsoft-zo-chatbot-goes-rogue-with-offensive-speech-tay-ai>.

Some Amazing Failures of AI (v): Impact on Real life

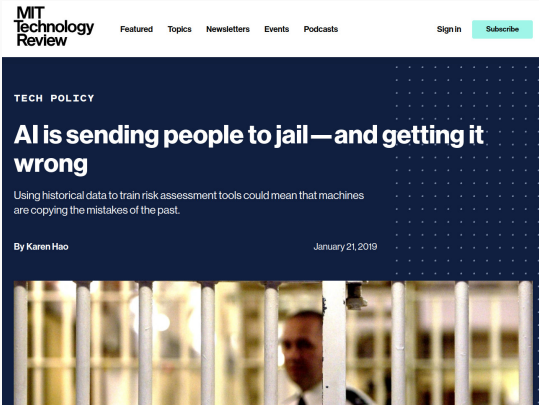


Figure 9: Source:

<https://www.technologyreview.com/2019/01/21/137783/algorithms-criminal-justice-ai/>

Examples: healthcare diagnostics, school outcome, etc.

Some Amazing Failures of AI (v): More on COMPAS

A computer program used for bail and sentencing decisions was labeled biased against blacks. It's actually not that clear.

By Sam Corbett-Davies, Emma Pierson, Avi Feller and Sharad Goel
October 17, 2016 at 5:00 a.m. EDT



Figure 10: Source: <https://www.washingtonpost.com/news/monkey-cage/wp/2016/10/17/can-an-algorithm-be-racist-our-analysis-is-more-cautious-than-propublicas/>

Examples of AI Models

Example: Decision Tree

```
library(rpart)
library (rpart.plot)

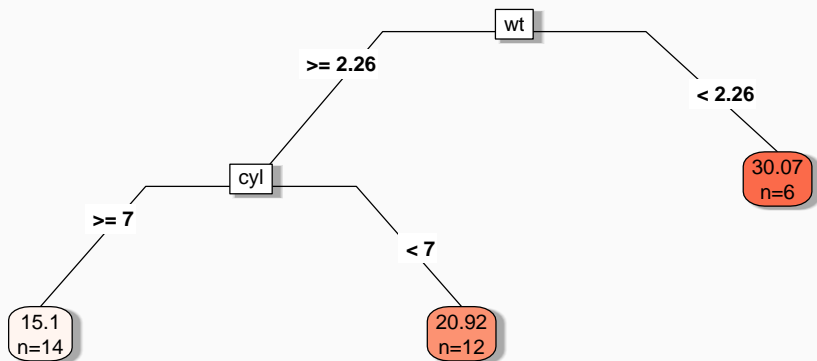
# Fit the tree:
t <- rpart(mpg ~ cyl + disp + hp + drat + wt + qsec + am + gear,
          data = mtcars, na.action = na.rpart, method = "anova",
          control= rpart.control(
    minsplit      = 10, # minimum nbr. of observations required for split
    minbucket     = 20/3, # minimum nbr. of observations in a terminal node
                  # the default = minsplit/3
    cp            = 0.0001, # complexity parameter set to a very small value
                  # his will grow a large (over-fit) tree
    maxcompete    = 4, # nbr. of competitor splits retained in output
    maxsurrogate  = 5, # nbr. of surrogate splits retained in output
    usesurrogate  = 2, # how to use surrogates in the splitting process
    xval          = 7, # nbr. of cross validations
    surrogatestyle = 0, # controls the selection of a best surrogate
    maxdepth     = 30 # maximum depth of any node of the final tree
  )
)
# omitted: investigate the optimal cutoff for the cost parameter cp

# Prune the tree:
t1 <- prune(t, cp = 0.05)
```

Visualise the Decision Tree

Plot the pruned tree:

```
prp(t1, type = 5, extra = 1, box.palette = "Reds",  
     digits = 4, shadow.col = 'darkgray', branch = 0.5)
```



Example: the Random Forest (i)

```
library(randomForest)

## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##   margin
frm      <- mpg ~ cyl + disp + hp + drat + wt + qsec + am + gear
set.seed(1879)

# Fit the random forest:
forestCars = randomForest(frm, data = mtcars)

# Show an overview:
print(forestCars)

##
## Call:
## randomForest(formula = frm, data = mtcars)
##           Type of random forest: regression
##           Number of trees: 500
## No. of variables tried at each split: 2
##
##           Mean of squared residuals: 6.001878
##           % Var explained: 82.94
```

Example: the Random Forest (ii)

```
getTree(forestCars, 1, labelVar=TRUE) # visualization of the RF

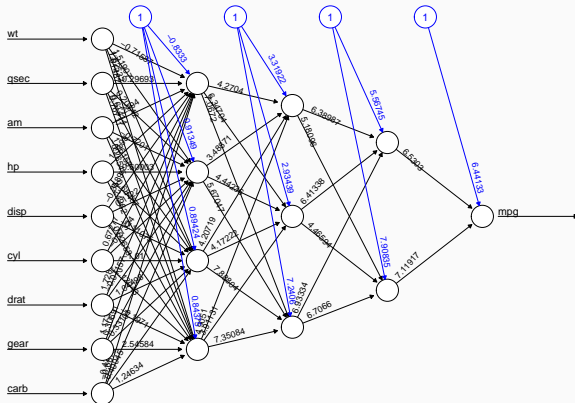
##   left daughter right daughter split var split point status prediction
## 1         2         3     disp    192.500   -3  20.75625
## 2         4         5     cyl     5.000   -3  24.02222
## 3         6         7     cyl     7.000   -3  16.55714
## 4         8         9     gear     3.500   -3  24.97857
## 5         0         0    <NA>     0.000   -1  20.67500
## 6         0         0    <NA>     0.000   -1  19.75000
## 7        10        11    qsec    17.690   -3  16.02500
## 8         0         0    <NA>     0.000   -1  21.50000
## 9        12        13    drat     4.000   -3  25.24615
## 10       14        15    drat     3.440   -3  16.53636
## 11        0         0    <NA>     0.000   -1  10.40000
## 12       16        17     am     0.500   -3  23.33333
## 13       18        19    qsec    19.185   -3  26.88571
## 14       20        21    drat     3.075   -3  17.67143
## 15        0         0    <NA>     0.000   -1  14.55000
## 16        0         0    <NA>     0.000   -1  23.44000
## 17        0         0    <NA>     0.000   -1  22.80000
## 18        0         0    <NA>     0.000   -1  24.68000
## 19        0         0    <NA>     0.000   -1  32.40000
## 20        0         0    <NA>     0.000   -1  15.80000
## 21        0         0    <NA>     0.000   -1  19.07500

importance(forestCars) # Show the purity of the nodes:

##      IncNodePurity
## cyl      163.83222
## disp    243.89957
## hp      186.24274
## drat     96.08086
## wt      236.59343
## qsec     57.99794
## am       31.84926
## gear     32.31675
```

Example: ANN

```
library(neuralnet)
# Fit the aANN with 3 hidden layers that have resp. 4, 3 and 2 neurons:
nn1 <- neuralnet(mpg ~ wt + qsec + am + hp + disp + cyl + drat + gear + carb,
                 data = mtcars, hidden = c(4,3,2), linear.output = TRUE)
plot(nn1, rep = "best", information = FALSE, arrow.length = 0.15);
```



Example SVN

```
library(e1071)
# split mtcars in two subsets (not necessary but easier later):
x <- subset(mtcars, select = -cyl)
y <- mtcars$cyl

# fit the model again as a classification model:
svmCars2 <- svm(cyl ~ ., data = mtcars, type = 'C-classification')

# create predictions
pred <- predict(svmCars2, x)

# show the confusion matrix:
table(pred, y)

##      y
## pred  4  6  8
##      4 11  0  0
##      6  0  7  0
##      8  0  0 14

svmTune <- tune(svm, train.x=x, train.y=y, kernel = "radial",
               ranges = list(cost = 10^(-1:2), gamma = c(.5, 1, 2)))
```

Example: k-means (clustering) – the code

```
# Normalize the whole mtcars dataset:
d <- data.frame(matrix(NA, nrow = nrow(mtcars), ncol = 1))
d <- d[,-1] # d is an empty data frame with 32 rows
for (k in 1:ncol(mtcars)) {
  rng <- range(mtcars[, k], na.rm = TRUE)
  d[, k] <- (mtcars[, k] - rng[1]) / rng[2]
}
colnames(d) <- colnames(mtcars)
rownames(d) <- rownames(mtcars)

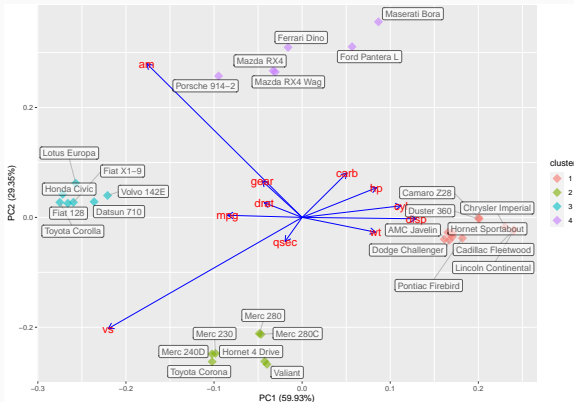
# The PCA analysis:
pca1 <- prcomp(d)

# Make the clustering:
carCluster <- kmeans(d, 4, nstart = 10)

d_cluster <- cbind(d, cluster = factor(carCluster$cluster))
```

Example: k-means (clustering) – the plot

```
autoplot(pca1, data = d_cluster, label = FALSE, shape = 18, size = 5,  
         alpha = 0.6, colour = 'cluster', loadings = TRUE, loadings.colour = 'blue',  
         loadings.label = TRUE, loadings.label.size = 5) +  
geom_label_repel(aes(label = rownames(mtcars)), force_pull = 0.01,  
                max.overlaps = 17, segment.color = 'grey60', alpha = 0.6)
```

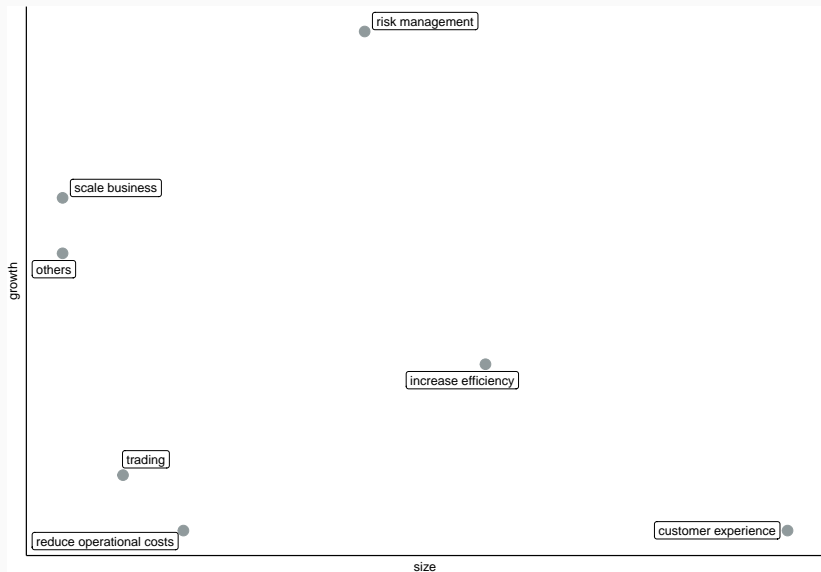


Practical Applications of AI

General Applications of AI

- regressions
- classifications
- clustering
- association analysis
- natural language processing (NLP)
- time series forecasting
- computer visions

Banking Applications of AI



Examples of Applications

- **Risk Management:**

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- **Scale Business:** digital marketing and campaign follow up
- **Increase efficiency:** bots, faster decisions, better decisions

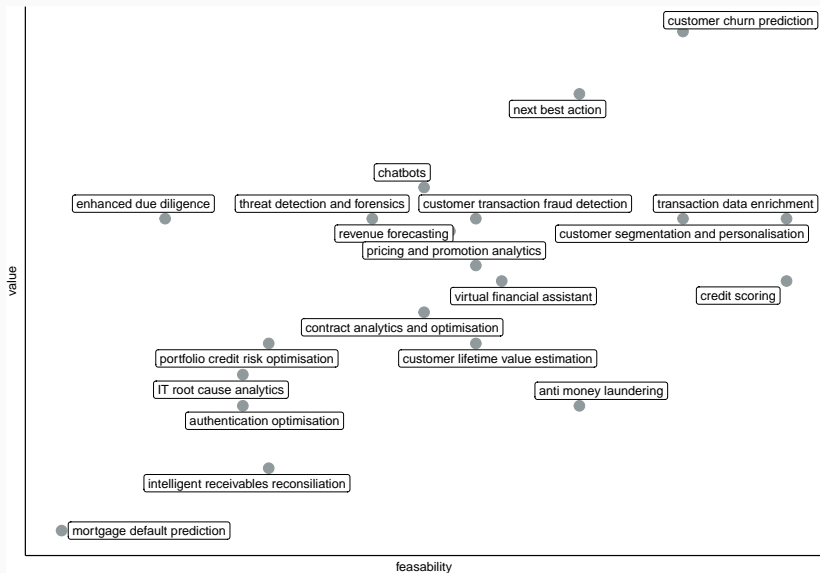
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- **Scale Business:** digital marketing and campaign follow up
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- **reduce operational costs:** process automation, decision intelligence, process screening
- **customer experience:** robo advisors, chatbots (e.g. BoA "Erica", HSBC "Amy", SEB "Aida")

Use Cases for AI in Banking



Use Case Example 1: Citigroup

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 - more reliable credit worthiness assessment

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- Results:
 - new products
 - new customers
 - lower false positive rate (hence less loss)
 - higher profit
 - effect on image as they "show empathy" and help customers in difficult situations

Use Case Example 2: UniCredit in Serbia

- Goal: increase sales via customer centric marketing

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- Method:

Use Case Example 2: UniCredit in Serbia

- Goal: increase sales via customer centric marketing
- Method:
 - the data science team integrated data from 8 sources

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 - more customers in difficult segments

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- Cultural differences (e.g. there is more trust towards AI in Germany than UK) – involve people early – be transparent

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Stay in control

Assure compliance with rules and regulations, enforce ethical standards, avoid the ING scenario (bad press because perceived improper use of data)

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 - How can we re-use the solution and learnings?

Example 1 of AI Governance – RBS

- RBS (Natwest) has a dedicated Data Science team that encompasses
 - the hardware
 - the data ingestion
 - the data structure and governance (lake, big data, structured data, golden source, use monitoring, passporing, etc.)
 - the analytics (dynamic dashboards, ad hoc decision support, mcda) with dedicated client centric teams for
 - Private Bank
 - Retail Bank
 - The rest

Example 2 of AI Governance – BNP Paribas

Dedicated “AI trust and risk management team”, closely collaborating with

- Model Risk Management
- conduct and compliance risk
- operational process risk and resilience
- data protection, cybersecurity, and privacy risk
- information security risk
- cloud and technology risk
- third party technology risk

The Future Impact of AI

The impact of AI will be proportional to how much we can re-invent and rethink the business itself

Conclusions

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- Consider the different phases and the AI CoE (see slide 38)

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