Kidbrooke Advisory

“We enable risk management.”
Who we are

- Founded in 2011, we are now 16 people based in Sweden and the UK
- Our clients are banks and insurance companies
- We focus on computational science with financial applications
## Our services

<table>
<thead>
<tr>
<th>Advisory services</th>
<th>Managed services</th>
<th>Analytics</th>
</tr>
</thead>
<tbody>
<tr>
<td>We provide advisory services covering a wide range of financial applications and aspects:</td>
<td>Pluggable toolbox of services or Process-as-a-Service (PaaS) to help financial institutions execute on their business models more efficiently</td>
<td>Standardised risk management Software-as-a-Service (SaaS) components</td>
</tr>
<tr>
<td>- Risk models</td>
<td>- Cost efficient cloud-based solutions</td>
<td>- Product rank - automated advice including end customer risk profiling</td>
</tr>
<tr>
<td>- Pricing and valuation</td>
<td>- Mitigation of key-person risk</td>
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<td>- Risk &amp; business insights</td>
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<td>- Regulatory expertise</td>
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Our Key Competences

**FINANCE & INSURANCE**
Our consultants have a strong skill set backed by an extensive track record
• Risk management
• ALM
• Asset management
• Regulatory frameworks

**TECHNOLOGY**
We have designed and built a number of large systems
• Calculation engines
• Integration platforms
• Data quality frameworks
• Automated processes

**MATHEMATICS**
We are skilled in mathematical modelling
• Risk models
• Valuation
• Regression & ML
• Model validation

**FINANCE**

**AGILE LEADERSHIP**

**TECH**

**MATHS**
Our background

Zaliia Gindullina
Business Developer
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M.Sc. Accounting and Financial Management
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M.Sc. Financial Markets and Financial Institutions
Higher School of Economics

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M.Sc. Mathematical statistics, Economics coursework
Lund University
Our mission

We democratise risk management
Case study
Automated Financial Advice
Background

Business challenges

- New regulatory requirements drive change
- Decreasing willingness to pay for investment management
- Financial firms express demand for cost-efficient multi-channel and digitised customer journeys
Regulations

- Increased transparency requirement w.r.t product cost
- Necessary to monitor:
  - Revenue streams
  - Product fee structures
- Investment firms required to specify value adding services with respect to end customers
  - Prioritised focus area for Swedish FCA throughout 2018
- Continuous prevention of possible conflicts of interest required
Willingness to pay

- Relentless focus on price
  - Launch of Avanza Global < 10 bps fee
- Some end customer segments are less hesitant than ever to switch their financial advisor based on cost
- Building trust to counter decreased willingness to pay is more important than ever
Case

Major Swedish Life-Insurer and Unit-Linked Platform

❖ Three year roadmap for digital advice
  ❍ Starting with digital pension advice
  ❍ End state will be full customer balance sheet advice

❖ Core risk and advice platform based on third party economic scenario generator and Kidbrooke “Product Rank”

❖ Model maintenance managed by Kidbrooke
How it works
Digital advice

- Figures/levels used in risk profile questions are calibrated using the scenario-set and general levels of wealth
- Compatible with a number of leading ESGs (e.g. Numerix, Ortec Finance, Moody’s Analytics)

- The savings goal and financial profile information is combined to recommend suitable investment amounts
- The risk profile can be extended with information about how actively a customer wants to monitor and manage his or her investments
- Risk profile calibration can be adapted to existing sets of risk profile questions

- The risk profile is represented via parameter values of the utility function
- The utility function itself and calibration of its parameters can be adapted to suit your needs
- The selection itself and attributes of the investments (fees, assumptions about value add, etc.) can easily be reviewed using the product rank functionality

- Utility is evaluated for each product and investment combination over all scenarios in the scenario-set
- Real time portfolio construction w.r.t. utility also possible

- The ranked products can optionally be subjected to further deterministic constraints before advising the customer to choose the investment with the highest utility

- Could be purpose-built by our consultants or delivered via SaaS
- Typically provided in-house or by a third party
- Kidbrooke Advisory SaaS or Managed Services
An advanced approach to risk profiling

The Industry Standard
Customers gain or lose points for each question assessing their risk appetite. These are later summed up with little regard to the nature of the questions and therefore peoples’ underlying attitude to risk

Example
- Risk Question I – Risk Tolerance Aspect I
  a) Low Risk Level Answer – 4 points
  b) Middle Risk Level Answer – 2 points
  c) High Risk Level Answer – 0 points
- Risk Question II – Risk Tolerance Aspect II
  a) Low Risk Level Answer – 4 points
  b) Middle Risk Level Answer – 2 points
  c) High Risk Level Answer – 0 points

Total Risk Aversion Level = Sum of Risk Points
If a customer selects a low risk level for Question I and a high risk level for Question II, which address different aspects of the risk profiling; the points system will not distinguish this customer from the one choosing a middle risk level for both Questions

The Kidbrooke State-of-the-art
Our advanced risk profiling methodology allows for distinguishing between a larger number of risk profiles. We assess the possible combinations of answers separately and therefore we achieve a more consistent and accurate risk profile

How do we do this?
1. We introduce risk tolerance intervals as the underlying result of the answer to each question;
2. We consider the consistency of the customers’ answers and weight the responses in accordance to the nature of the question;
3. We calculate the individual risk tolerance weighting and summing up the results of responses, capturing the unique client risk appetite accurately.

Bottom line:
✔ Individual approach to end customers
✔ Enhanced approach to risk profiling
✔ Consistent treatment of risk

Why is this important to a financial firm?
More granular approach to risk appetite assessment enhances the quality of advice

Fast track to customer satisfaction

Sustainable value creation
Comparative study

Least-Squares Monte Carlo vs. Artificial Neural Networks
Least-squares Monte Carlo
A 2-step procedure

1. Nested Monte Carlo simulation of outer and inner scenarios
   a) **Outer scenarios**
      Generated under real world measure
   b) **Inner scenarios**
      Generated under risk neutral measure, used to valuate each instrument conditional on the generated risk factors.
      Scenario value = averaged inner scenarios
Least-squares Monte Carlo
A 2-step procedure

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   a) **Outer scenarios**
      Generated under real world measure
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      Generated under risk neutral measure, used to valuate each instrument conditional on the generated risk factors
      Scenario value = averaged inner scenarios

2. Least-squares regression over averaged inner scenarios
   ⇒ obtain LSMC proxy function
LSMC - VaR of European put option

Value-at-Risk (VaR):

\[ \text{VaR}_\alpha = 1 - \alpha \text{-percentile of return distribution, or } \alpha \text{-percentile of loss distribution:} \]

\[ \text{VaR}_\alpha(l) = F_L^{-1}(\alpha) = \inf \{ l \in \mathbb{R} \mid F_L(l) \geq \alpha \}, \quad \alpha \sim [0, 1] \]

Fig: VaR of demeaned return distribution.
Step 1: Nested simulation

Outer scenarios:
Simulate \( m = 1, \ldots, N_{outer} \) stock process \( S_t^m \) up until \( t_{outer} = 1 \) year.

Inner scenarios:
Starting from each outer scenario, simulate \( n = 1, \ldots, N_{inner} \) inner stock processes (\( N_{inner} << N_{outer} \)) up until \( t_{inner} \).

Put option value:
\[
\pi(t_{outer}, S_{inner}^m, K) = \frac{1}{N_{inner}} \sum_{n=1}^{N_{inner}} e^{-\int_{t_{outer}}^{t_{inner}} r(s) ds} \max(K - S_{inner}^n, 0)
\]
LSMC - VaR of European put option

Step 2: Least-squares regression

\[ Y = \pi(t_{outer}, S_{inner}^m, K), \ m = 1, \ldots, N_{outer} \]
\[ X = [1, (S_{outer}^m)^1, (S_{outer}^m)^2, \ldots] \]
\[ Y = X\beta + \epsilon \Rightarrow \hat{\beta} = (X^T X)^{-1} X^T Y \]

- LSMC proxy function: \( f(\hat{\beta}, S_{outer}^m) \)
- No inner scenarios required:
  \[ \hat{\pi}(t_{outer}, S_{inner}^m, K) = f(\hat{\beta}, S_{outer}^m) \]
- VaR obtained from quantiles of option value distribution.
Why LSMC?

• Vast reduction of inner scenarios ⇒ significant gain in time efficiency

• High accuracy

• Allows for an increased complexity

E.g. for pricing path dependent options with multiple sources of uncertainty, where an analytical solution is impractical or impossible.
Alternative to LSMC: Machine learning

Vast increase of available data $\Rightarrow$ increased interest in automated methods of data analysis.

Machine learning (ML) learns from previous data and develops its own predictive capacity through various algorithms and techniques.

Highly flexible and computationally efficient ML algorithm able to capture non-linear patterns in data:

Artificial neural networks (ANN)
Artificial neural networks

ANN applied to regression:

\[ X \xrightarrow{\sigma(.)} Z_m \xrightarrow{g_k(.)} f_k(X) \]

- Often multiple layers of nodes, referred to as hidden layers
- Output \( f_k(X) \) is a function \( g_k \) of the \( Z_m \)'s of the last hidden layer

Fig. One hidden layer-ANN with two input nodes, three hidden nodes, and one output node.
Artificial neural networks

One hidden layer-ANN:

\[ Z_m = \sigma(\alpha_0 m + \alpha_m^T X), \ m = 1, \ldots, M, \]
\[ T_k = \beta_0 k + \beta_k^T Z, \ k = 1, \ldots, K, \]
\[ f_k(X) = g_k(T), \ k = 1, \ldots, K, \]

where \( Z = (Z_1, Z_2, \ldots, Z_m), T = (T_1, T_2, \ldots, T_k) \) with \( M = \) # nodes in hidden layer and \( K = \) # output nodes

Activation functions

- Sigmoid function: \( \sigma(v) = \frac{1}{1 + e^{-v}} \)
- Rectifier linear unit (ReLU) function: \( \sigma(v) = \max[v, 0] = v^+ \)

Output function

- Identity function: \( g_k(x) = x_k \)
Artificial neural networks

Aim: Find parameter values $\alpha_0, \alpha_m, \beta_{0k}$ and $\beta_{0k}$.
• Referred to as "training" the model.
• Main idea: Fit data to training set to predict outcomes on separate test set while minimizing squared error $R(\theta)$:

$$R(\theta) = \sum_{k=1}^{K} \sum_{i=1}^{N} (y_{ik} - f_k(x_i))^2$$

Method: Gradient descent.
• For this kind of ANN: Backpropagation algorithm.
1. Set of weights:
   Weight set $\theta$
   
   $\alpha_{om}, \alpha_m; \ m = 1, 2, ..., M, \rightarrow M(p + 1)$ weights
   $\beta_{0k}, \beta_k; \ k = 1, 2, ..., K, \rightarrow K(M + 1)$ weights

2. Square error:
   
   $R(\theta) = \sum_{k=1}^{K} \sum_{i=1}^{N} (y_{ik} - f_k(x_i))^2$

3. Partial derivatives:
   
   $\frac{\partial R_i}{\partial \beta_{km}} = -2(y_{ik} - f_k(x_i)g_k(\beta_k^T z_i)z_{mi}$
   $\frac{\partial R_i}{\partial \alpha_{ml}} = -\sum_{k=1}^{K} 2(y_{ik} - f_k(x_i))g_k(\beta_k^T z_i)\beta_{km}\sigma'(\alpha_m^T x_i)x_{il}$

4. Gradient descent iterations:
   
   $\beta_{km}^{t+1} = \beta_{km} - \gamma r \sum_{i=1}^{N} \frac{\partial R_i}{\partial \beta_{km}}$
   $\alpha_{ml}^{t+1} = \alpha_{ml} - \gamma r \sum_{i=1}^{N} \frac{\partial R_i}{\partial \alpha_{ml}}$

5. ANN current errors:
   
   $\delta_{ki} = -2(y_{ik} - f_k(x_i)g_k(\beta_k^T z_i)$
   $s_{mi} = -\sum_{k=1}^{K} 2(y_{ik} - f_k(x_i))g_k(\beta_k^T z_i)\beta_{km}\sigma'(\alpha_m^T x_i)$

6. Rewrite partial derivatives from 3:
   
   $\frac{\partial R_i}{\partial \beta_{km}} = \delta_{ki} z_{mi}$
   $\frac{\partial R_i}{\partial \alpha_{ml}} = s_{mi} x_{il}$

7. Backpropagation equations:
   
   $s_{mi} = \sigma'(\alpha_m^T x_i) \sum_{k=1}^{K} \beta_{km}\delta_{ki}$

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*"The Elements of Statistical Learning: Data Mining, Inference, and Prediction" Tibshirani et al, 2009*
Error minimization

- **Bias error**: Complexity too low ⇒ model unable to identify all the underlying structures of the data.
- **Variance error**: Overfitted model ⇒ low degree of generalization.

Fig: Illustration of underfitting with large bias error (left), a good fit (middle) and overfitting with large variance error (right).
**Variance error:** Overfitted model ⇒ low degree of generalization.

**Possible solutions**

- **Dropout:** (ANN) Randomly removes hidden nodes from model during training.

- **Regularization:** Penalizes large weights.

$L^2$ regularization for an ANN:

\[
Loss = Error\ function + \lambda \sqrt{\sum_{m=1}^{M} \alpha_m^2 + \sum_{k=1}^{K} \beta_k^2},
\]

$\lambda = \text{weight regularization factor.}$
Comparative study

LSMC vs. ANN

Task:
Calculating 1-year $\text{VaR}_{99.5\%}$ of European option portfolio
Solvency Capital Requirement (SCR)

- SCR: 99.5% 1-year VaR
- Required according to Solvency II regulations for all insurance companies
- Helps understand risk profile
- Efficient tool in risk mitigation
LSMC vs. ANN

Mixed option portfolio:

- Time to maturity = 2 years
- Moneyness = Strike price / Spot price
- P/C specifies put (P) or call (C) option
- # specifies number of options in portfolio
- L/S specifies long (L) or short (S) option position

<table>
<thead>
<tr>
<th>Option</th>
<th>Moneyness</th>
<th>P/C</th>
<th>#</th>
<th>L/S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Option 1</td>
<td>120</td>
<td>C</td>
<td>3</td>
<td>L</td>
</tr>
<tr>
<td>Option 2</td>
<td>113.75</td>
<td>C</td>
<td>4</td>
<td>L</td>
</tr>
<tr>
<td>Option 3</td>
<td>110</td>
<td>C</td>
<td>6</td>
<td>L</td>
</tr>
<tr>
<td>Option 4</td>
<td>107.5</td>
<td>C</td>
<td>2</td>
<td>L</td>
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<tr>
<td>Option 5</td>
<td>105</td>
<td>C</td>
<td>4</td>
<td>L</td>
</tr>
<tr>
<td>Option 6</td>
<td>102.5</td>
<td>C</td>
<td>4</td>
<td>L</td>
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<tr>
<td>Option 7</td>
<td>100</td>
<td>P</td>
<td>1</td>
<td>L</td>
</tr>
<tr>
<td>Option 8</td>
<td>97.5</td>
<td>P</td>
<td>2</td>
<td>L</td>
</tr>
<tr>
<td>Option 9</td>
<td>95</td>
<td>P</td>
<td>1</td>
<td>L</td>
</tr>
<tr>
<td>Option 10</td>
<td>92.5</td>
<td>P</td>
<td>2</td>
<td>L</td>
</tr>
<tr>
<td>Option 11</td>
<td>90</td>
<td>P</td>
<td>2</td>
<td>L</td>
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<tr>
<td>Option 12</td>
<td>87.5</td>
<td>P</td>
<td>3</td>
<td>L</td>
</tr>
<tr>
<td>Option 13</td>
<td>85</td>
<td>P</td>
<td>5</td>
<td>L</td>
</tr>
<tr>
<td>Option 14</td>
<td>78.75</td>
<td>P</td>
<td>2</td>
<td>L</td>
</tr>
<tr>
<td>Option 15</td>
<td>70</td>
<td>P</td>
<td>5</td>
<td>L</td>
</tr>
</tbody>
</table>

Fig: Pay-off at time $t = 2$ years for different stock price outcomes.
Scenario generation

**Stock process:**

Bates (SVJD) model - includes both stochastic volatility and a compounded jump process.

**Short rate process:**

Hull-White model - mean reverting, can be calibrated to fit initial term structure of forward rate.

**Correlation:**

Assumed between Brownian motions of stock and short rate processes. Calibrated from OMSX30 index and STIBOR 3 month rate, respectively.
LSMC vs. ANN
Evaluation & comparison

Full nested:
# outer scenarios: 10 000
# inner per outer scenarios: 10 000

LSMC: Number of *inner* scenarios reduced
# outer scenarios: 10 000
# inner per outer scenarios: 10

ANN: Number of *outer* scenarios reduced
# outer scenarios: 200*
# inner per outer scenarios: 10 000
LSMC
Evaluation & comparison

**LSMC**: Number of *inner* scenarios reduced

- # outer scenarios: 10,000
- # inner per outer scenarios: 10

  - Calibration to LSMC set to obtain LSMC proxy function
  - Evaluation: Full nested outer scenarios used as input to proxy function and compared to full nested inner values
ANN
Evaluation & comparison

**ANN:** Number of **outer** scenarios reduced

- # outer scenarios: 100
- # inner per outer scenarios: 10,000
  - Training set

- # outer scenarios: 100
- # inner per outer scenarios: 10,000
  - Test set

- # *outer scenarios: 9,800
- # inner per outer scenarios: 0
  - Prediction set

• Values from prediction set compared to full nested inner values
LSMC vs. ANN

ANN goodness of fit: Regularization

Loss = Error function + \( \lambda \sqrt{\Sigma_{m=1}^{M} \alpha_m^2 + \Sigma_{k=1}^{K} \beta_k^2} \)

\( \lambda \) = weight regularization factor.

Fig: Impact on the error of varying \( \lambda \) in the loss function during ANN training.
LSMC vs. ANN

Results

Table 1: Performance of the ANN (100 runs) and LSMC approach with the full nested simulation as benchmark.

<table>
<thead>
<tr>
<th>Model</th>
<th>$R^2$</th>
<th>% RMSE</th>
<th>Estimated SCR</th>
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<tbody>
<tr>
<td>Full nested</td>
<td>-</td>
<td>-</td>
<td>1614.58</td>
</tr>
<tr>
<td>ANN</td>
<td>0.9989</td>
<td>4.94 (Min)</td>
<td>1582.02 (Min)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.44 (Mean)</td>
<td>1615.64 (Mean)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>6.64 (Max)</td>
<td>1639.77 (Max)</td>
</tr>
<tr>
<td>LSMC 3 deg</td>
<td>0.9168</td>
<td>47.81</td>
<td>1589.04</td>
</tr>
<tr>
<td>LSMC 6 deg</td>
<td>0.9287</td>
<td>44.26</td>
<td>1722.79</td>
</tr>
<tr>
<td>LSMC 10 deg</td>
<td>0.9643</td>
<td>31.31</td>
<td>1602.81</td>
</tr>
<tr>
<td>LSMC 15 deg</td>
<td>0.9626</td>
<td>32.05</td>
<td>1602.79</td>
</tr>
<tr>
<td>LSMC 20 deg</td>
<td>0.9610</td>
<td>32.74</td>
<td>1689.13</td>
</tr>
<tr>
<td>LSMC 25 deg</td>
<td>0.9422</td>
<td>39.88</td>
<td>1677.65</td>
</tr>
</tbody>
</table>

Table 2: Computation time using full nested simulation, ANN approach and LSMC approach.

<table>
<thead>
<tr>
<th>Model</th>
<th>Computation time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full nested</td>
<td>1357.86 seconds</td>
</tr>
<tr>
<td>ANN</td>
<td>81.33 seconds</td>
</tr>
<tr>
<td>LSMC</td>
<td>104.2 seconds</td>
</tr>
</tbody>
</table>
LSMC vs. ANN

LSMC results for different polynomial degrees

Fig: Prediction accuracy of LSMC approach for different polynomial degrees.
LSMC vs. ANN

Conclusion

• ANN outperforms LSMC both in terms of accuracy and time performance

• Similar studies: ANN shown to be particularly good for data sets with higher dimensions and more complex relationships between variables\(^1\)

Applications

• Path dependent option pricing\(^2\)

• SCR calculations\(^3\)

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\(^1\)“Deep Neural Networks for High Dimension, Low Sample Size Data” Liu, B. et al. (2017).


What can we offer you?

Graduate opportunities at Kidbrooke Advisory

• Thesis work
• Full time junior consulting positions
Write your master’s thesis with us
Applicant evaluation process

CONTACT US
• Get in touch!
• Visit our homepage
• Send us an email at: info@kidbrooke.com

INITIAL INTERVIEW
• Usually held over phone
• Tell us who you are
• Info about Kidbrooke
• Thesis topics

TECHNICAL TEST
• Technical test distributed over email
• Focus on mathematical statistics

MEET THE TEAM
• Meet our team at the office in Stockholm
• Follow up on technical test

OFFER
• Thesis scope
• Appointment of supervisor
Kidbrooke Advisory

We enable risk management.

info@kidbrooke.com

Please visit our website for more information and several in-depth case studies of client achievements

https://kidbrooke-advisory.com/