AGENCY MBS PREPAYMENT MODEL USING NEURAL NETWORKS

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David Zhang
MSCI Securitized Products Research
David Zhang is a Managing Director and Head of Securitized Products Research at MSCI. His team is responsible for developing models and analytics to support investment analysis, risk management, and regulatory compliance. Before joining MSCI, Dr Zhang was Managing Director and head of Securitized Products modeling at Credit Suisse for more than a decade. At Credit Suisse he was responsible for supporting risk, regulatory and client analytics as well as sales/trading quantitative strategies. Dr Zhang’s group developed one of the most widely used MBS models by fixed income institutional investors. Their work was consistently awarded top ranking by various industry and client surveys, including Institutional Investor All-America Research Team ranking in Agency prepayment. They also won the award for best paper by the American Real Estate Society for research on effectiveness of government mortgage programs. The regulatory projects Dr Zhang lead at Credit Suisse included developing models for CCAR and PPNR (Pre-Provision Net revenue), Dodd-Frank IHC (Intermediate Holding Company) and related VaR, RWA and RBPL modeling, and FRTB (Fundamental Review of Trading Book). Prior to Credit Suisse, Dr Zhang worked at FreddieMac, CIBC Oppenheimer, and University of Chicago. He holds leadership positions at PRMIA (Professional Risk Management International Association) and GCREC (Global Chinese Real Estate Congress). He is a frequent speaker at industry and academic conferences, and his research on risk, financial modeling and real estate has been published in many academic journals. Dr Zhang has a Ph.D. from Princeton University.
Why a machine learning model for Agency MBS?

- Prepayment is a highly complex and non-linear process with many idiosyncratic risk factors, among the most complex financial models
- Recent development in computational software and hardware enable us to make significant advancement in AI prepayment models
- Machine learning models have excelled in many areas, such as image recognition, natural language processing, fraud detection, etc.

What is the model and what have we learned?

- Deep neural network model applied to pool level agency MBS prepayment data, compared with MSCI1 (the human model)
- Results show the deep learning model is able to capture very complex prepayment patterns and signals with extremely high computational efficiency
• Consumer credit risk models via Machine-Learning Algorithms (Dr. Andrew Lo, 2010)
  Using machine-learning model for consumer credit default and delinquency
  Generalized classification and regression trees
  Accurately forecasted credit events 3 to 12 months in advance

• Risk and risk management in credit card industry (Dr. Andrew Lo, 2016)
  Analyzed very large dataset consisting of credit card data from six large banks.
  Decision trees and random forests model perform better than logistic regression at short time horizon

• Deep learning for mortgage risk (Dr. Kay Giesechke, 2015-2018)
  Using deep neural network to model mortgage prepayment, delinquency and foreclosure
  Loan level data
  Compared NNM with a logit model
US BOND MARKET

US Bond Market 2018 (42.4$Tn)

- Corporate Debt: 9.16%
- Treasury: 15.27%
- Municipal: 3.83%
- Mortgage Related: 9.66%
- Federal Agency Securities: 1.87%
- Money Markets: 1.05%
- Asset-Backed: 1.56%
- Agency MBS: 8.27%
- Non-Agency MBS: 1.39%

US Bond Market 2007 (29.5$Tn)

- Corporate Debt: 5.33%
- Treasury: 4.52%
- Municipal: 3.55%
- Mortgage Related: 9.39%
- Federal Agency Securities: 2.91%
- Money Markets: 1.79%
- Asset-Backed: 1.96%
- Agency MBS: 5.80
- Non-Agency MBS: 3.58%
Forecast prepayment rate for agency RMBS pools

**SMM**: Single Monthly Mortality Rate

**CPR**: Conditional Prepayment Rate

Agencies report last month’s prepayment speed on the 4\textsuperscript{th} business day of each month.

Prepayment types:
- Rate refinance
- House turnover
- Cash-out
- Curtailment
- Buyout
Difficulties with mortgage prepayment modeling

- Large data sets: ~20-2000 G data, Agency MBS covers ~400,000 pools/100+mm loans performance over 20-30 years, pool/loan variables ~30-100

- Multiple, highly non-linear and interactive risk drivers ("layered risk")
  - Loan size vs. prepayment is function of moneyness
  - Age vs. prepayment is function of past moneyness history
  - Loan purpose (refi vs purchase) vs. prepayment is function of origination year
  - ....

- Regime changes
  - Mortgage credit and borrower risk appetite cycles, and business practice affect absolute level and risk drivers for prepayment/default
Agency MBS prepayment

- Complex behaviors
  - 30–100 risk factors: rates, loan size, GEO, purpose, property, HPA...
  - “layered risk”- non-linear interaction (e.g., loan size vs moneyness, purpose vs. origination year, ..)
  - Regime changes: behavior, policy
  - Statistical noises

- Large data set to model
  - 400,000 pools/100m loans, 30yr

- Modelers as craftsman?
  - Idiosyncratic modeler risk
AI agency MBS prepayment model

Deep neural network model

- Feed forward neural network
  - Applied successfully in many other fields
  - Layers and nodes, hyper-parameters
  - Ensemble techniques, bagging and boosting

- Competing vs. “human” /MSCI production model
  - Forecast accuracy
  - New signals, new discoveries
  - x100-1000 Efficiency gains: 3hrs vs. weeks/months
AI vs. “human” models: higher accuracy

- Higher modeling accuracy
  - Across cohorts and multiple dimensions of risk factors
  - Highly adaptive to high dimensionality and non-linearity
AI vs. “human” models: higher accuracy

**FICO**

- **Actual**
- **NNM**

<table>
<thead>
<tr>
<th>FICO</th>
<th>Pre-2008</th>
<th>Post-2008</th>
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<tbody>
<tr>
<td>720</td>
<td>740</td>
<td>760</td>
</tr>
<tr>
<td>720</td>
<td>740</td>
<td>760</td>
</tr>
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</table>

**SATO**

- **Actual**
- **NNM**

<table>
<thead>
<tr>
<th>SATO</th>
<th>Pre-2008</th>
<th>Post-2008</th>
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</thead>
<tbody>
<tr>
<td>0</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>20</td>
<td>30</td>
<td>40</td>
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**Current loan size**

- **Actual**
- **NNM**

<table>
<thead>
<tr>
<th>Current loan size</th>
<th>50,000</th>
<th>100,000</th>
<th>150,000</th>
<th>200,000</th>
<th>250,000</th>
<th>300,000</th>
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<tbody>
<tr>
<td>CPR</td>
<td>0</td>
<td>5</td>
<td>10</td>
<td>15</td>
<td>20</td>
<td>25</td>
<td>30</td>
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</table>

**CLTV**

- **Actual**
- **NNM**

<table>
<thead>
<tr>
<th>CLTV</th>
<th>55</th>
<th>65</th>
<th>75</th>
<th>85</th>
<th>95</th>
<th>105</th>
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<tbody>
<tr>
<td>CPR</td>
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<td>5</td>
<td>10</td>
<td>15</td>
<td>20</td>
<td>25</td>
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</table>
AI vs. “human” models: higher accuracy

- Higher modeling accuracy
  - Across cohorts and multiple dimensions of risk factors
  - Highly adaptive to high dimensionality and non-linearity
AI vs. “human” models: higher accuracy

- “Media effect”
  - When rates hit historical low, new & lower coupons ramp up faster
  - Highly non-linear behavior and depends on multiple risk factors
AI vs. “human” models: new signals

- Accuracy vs overfitting: loan size example
  - Understand sensitivities of risk drivers and economic rationale
  - Apply regularization to penalize overfitting
AI vs. “human” models: new signals

• Is low loan balance still safe investment for extension risk?
  – Sensitivity tests for the AI model indicate relationship between loan size and housing turnover has flipped after the recession
  – This is verified by Black Knight’s proprietary data

Model speeds for OTM 60bps vs loan size (in thousands)

Housing turnover vs loan size and year*

* Source: Black Knight, used with permission
NN model vs. “Human Model”

• Accurate forecasts and successfully flag prepayment anomalies *over the study period*
• Accurate model large numbers of risk factors
• Accurate model highly non-linear and interactive risk factors
• Highly efficient modeling process - hundreds times of increases in modeling efficiency
• *Was* able to find/flag prepayment signals that eluded human models
Joy Zhang:
Executive Director, Securitized Product Research, MSCI

Jan Zhao:
Principal, Advanced Analytics, Ernst & Young

Fei Teng:
Senior Quantitative Analysts, Quantitative Advisory Services, Ernst & Young

Siyu Lin:
Senior Quantitative Analysts, Quantitative Advisory Services, Ernst & Young

Henry Li:
Executive Director, in Quantitative Advisory Services practice, Ernst & Young
Appendix
Exhibit 4: Agency MBS prepayment regimes since 2003

2003: historical low mortgage rates and refinancing wave

Mid 2004–Mid 2006: Strong home price appreciation (HPA), fast housing turnover, high cash out refinancing and fast discount prepayment speed

Mid 2007–2009: Severe home price depreciation (HPD), low housing turnover, no cash out refinancing and slow rate term refinancing

2009: historical low mortgage rates, but muted refinancing response. High premium coupons prepay ever slower than lower premium coupons, because of much tighter lending standard for weaker borrowers

FN 30 CPR / Rate Incentive Bracket (Age = 10–30)

CPR

Month

Jan-03 Aug-03 Mar-04 Nov-04 Jun-05 Jan-06 Sep-06 Apr-07 Nov-07 Jul-08 Feb-09 Oct-09

(-50, -25) (75, 100) (150, 175)
The HARP program caused temporary inversion of the CLTV Prepayment Curve.

HARP: Home Affordable Refinance Program
V2002 Major Premium Coupons At 2003 Refi Wave

In 2003 refi wave, higher coupons prepay faster. But in 2009 refi wave, higher coupons prepay slower. The weaker credit quality of higher coupons was not much an issue in 2003’s refi, but it become a big refi hurdle in 2009’s refi.

CPR

Month

Jan-03 Feb-03 Mar-03 Apr-03 May-03 Jun-03 Jul-08 Aug-08 Sep-08 Oct-08 Nov-08 Dec-08

V2008 Major Premium Coupons At 2009 Refi Wave

In 2003 refi wave, higher coupons prepay faster. But in 2009 refi wave, higher coupons prepay slower. The weaker credit quality of higher coupons was not much an issue in 2003’s refi, but it become a big refi hurdle in 2009’s refi.

CPR

Month

Jan-09 Feb-09 Mar-09 Apr-09 May-09 Jun-09 Jul-09 Aug-09 Sep-09 Oct-09
MORTGAGE PREPAYMENT MODELING: SCIENCE AND CRAFTSMANSHIP

FN30 6.0 V2004 CPR / Fico (owner occ, clsz=100K-150K, oltv < 80)

- Seasoned loan's FICO picks up importance again in tight lending environment
- FICO becomes less important after a few years' seasoning
- Higher FICO prepays faster for new mortgages

680-720
> 720
Example of modeling:
Assume ppm (pool, time) = f(X1, X2, X3, .... Xn) ...

start by assuming separable risk factor: ppm= f1(x1)*f2(x2).... Until (often) proven incorrect...

estimating f1(x1) by “building cohort”, by bucketing loans/pools for groups of x1, but similar x2, x3....
(this further assumes quasi linear property of x2, x3.... Average(f2(x2) f3(x3)...) = f2(ave(x2))*f3(ave(x3))....

..... Checking overall fit after all Xn are fitted, adding extra variables to deal with non-linear and interactive variables... this often does not lead to convergence ...

• Time consuming and non-standard approaches
• Experience and step-by-step / regime-by-regime progress are valued
• Can new techniques of AI modeling provide the much needed disruption?
Network architecture:

Layers and nodes

Hyper-parameters
  Batch size, number of nodes, learning rate, max-norm constraint, dropout rate

Ensemble techniques:
  Bagging: minimum MSE of different realizations and neural networks
  Boosting: Fine tune a neural network via changing a few hyper-parameters
# Traditional vs. Deep Machine Learning

<table>
<thead>
<tr>
<th>Traditional Learning Algorithm</th>
<th>Pros</th>
<th>Cons</th>
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</thead>
<tbody>
<tr>
<td>Works better on smaller data</td>
<td></td>
<td>Hard to scale</td>
</tr>
<tr>
<td>Financially and computationally cheap</td>
<td></td>
<td>Lack of variability</td>
</tr>
<tr>
<td>Algorithms are easier to interpret, have more theories to back them up</td>
<td></td>
<td>Labor intensive model maintenance</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Deep Learning</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>state-of-the-art for certain domains, such as computer vision and speech recognition.</td>
<td>require large amount of data.</td>
</tr>
<tr>
<td></td>
<td>Perform very well on image, audio, and textual data, Easily updated with new data</td>
<td>Not suitable for classical machine learning problems.</td>
</tr>
<tr>
<td></td>
<td>Versatile architecture and low overhead maintenance</td>
<td>Computationally intensive to train, and they require much more expertise to tune</td>
</tr>
</tbody>
</table>

![Model Performance Graph](image)
Feed forward neural network (FNN)

the information moves in only forward direction from the input nodes to the output nodes. There are no cycles or loops in the network.

Deep FNN consists of tens of layers and thousands of nodes; the simplest kind of FNN is logistic model

Recurrent Neural Network (RNN)

A class of neural networks exploit the historical input sequences. Such inputs could be text, speech, time series, and anything else where the occurrence of an input in the sequence is dependent on the inputs that appeared before it

Motivation: Not all problems can be converted into one with fixed length inputs and outputs, such as text translation, speech recognition or time-series; predictions require a system to store and use context information

The input at time $t$ include both the attributes at $t$ and the intermediate values containing history at $t-1$. 
Deep neural network fitting

2003-2018 30yr agency MBS data (~25G data)

30+ input variables: pool attributes, macro-economic variables

To reduce complexity, we added incentive, 1 regime indicators, and 1 policy indicator (HARP)

Cost function of RMS error of pool level prepayment

1 round of fitting can be completed in ~ 3 hours on a GPU machine
### MODEL DRIVERS

#### Independent variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>WALA</td>
<td>Weighted Average Loan Age</td>
</tr>
<tr>
<td>WAC</td>
<td>Weighted Average Coupon</td>
</tr>
<tr>
<td>CLNSZ</td>
<td>Current Average Loan Size</td>
</tr>
<tr>
<td>OLTV</td>
<td>Original Loan to Value</td>
</tr>
<tr>
<td>Refi%</td>
<td>Percentage of Refinanced Loans by UPB</td>
</tr>
<tr>
<td>SecHome%</td>
<td>Percentage of Second Home Loans by UPB</td>
</tr>
<tr>
<td>MultiFamily%</td>
<td>Percentage of Multi Family Loans by UPB</td>
</tr>
<tr>
<td>Investor%</td>
<td>Percentage of Investor Loans by UPB</td>
</tr>
<tr>
<td>TPO%</td>
<td>Percentage of Third party origination by UPB</td>
</tr>
<tr>
<td>AOL</td>
<td>Original Average Loan Size</td>
</tr>
<tr>
<td>LNSZ_Q4</td>
<td>Max original loan size</td>
</tr>
<tr>
<td>LNSZ_Q3</td>
<td>Max original Loan Size - 3rd Quartile</td>
</tr>
<tr>
<td>LNSZ_Q1</td>
<td>Max original Loan Size - 1st Quartile</td>
</tr>
<tr>
<td>Geo_CA%</td>
<td>Percentage of California Loans by UPB</td>
</tr>
<tr>
<td>Geo_FL%</td>
<td>Percentage of Florida Loans by UPB</td>
</tr>
<tr>
<td>Geo_TX%</td>
<td>Percentage of Texas Loans by UPB</td>
</tr>
<tr>
<td>Geo_NY%</td>
<td>Percentage of New York Loans by UPB</td>
</tr>
<tr>
<td>Geo_NE%</td>
<td>Percentage of New England Region Loans by UPB</td>
</tr>
<tr>
<td>Geo_NO%</td>
<td>Percentage of North Region Loans by UPB</td>
</tr>
<tr>
<td>Geo_SO%</td>
<td>Percentage of South region Loans by UPB</td>
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<tr>
<td>Geo_PC%</td>
<td>Percentage of Pacific region Loans by UPB</td>
</tr>
<tr>
<td>Geo_AT%</td>
<td>Percentage of Atlantic region Loans by UPB</td>
</tr>
<tr>
<td>Geo_NONUS%</td>
<td>Percentage of non-US region Loans by UPB</td>
</tr>
<tr>
<td>Seasonality</td>
<td>Calendar month</td>
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</table>

#### Derived Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Formula</th>
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<tbody>
<tr>
<td>Incentive</td>
<td>WAC - Mortgage Rate(t)</td>
</tr>
<tr>
<td>Rolling Incentive</td>
<td>Average Incentive ( 20month) ( \sum_{t=1}^{20, \text{wal}a} \frac{\text{Incentive}}{\text{min}(20, \text{wal}a)} )</td>
</tr>
<tr>
<td>Loan size dispersion</td>
<td>(LNSZ_Q3-LNSZ_Q1)/AOL</td>
</tr>
<tr>
<td>SATO</td>
<td>Spread-at_origination = WAC - Mortgage Rate(0)</td>
</tr>
<tr>
<td>HPA</td>
<td>House Price Appreciation ( ( \frac{\text{HPI}(t)}{\text{HPI}(0)} - 1 ) )</td>
</tr>
<tr>
<td>HARP-able</td>
<td>2: IssueMonth &lt;= Jun. 2009 and factor date &gt; Dec. 2011</td>
</tr>
<tr>
<td>HARP-ed</td>
<td>Refi% = 100 and OLTV &gt; 80 and issueMonth &gt; Jun. 2009</td>
</tr>
<tr>
<td>Underwriting standard</td>
<td>0: before 2008, 1: after 2008</td>
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</table>

#### Weight

<table>
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<tr>
<th>Variable</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>cBal</td>
<td>Current Balance</td>
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#### Dependent Variable

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
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<tbody>
<tr>
<td>Prepayment speed</td>
<td>Prepayment speed in SMM</td>
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</table>
Error tracking is generated using out-of-the-sample pools.
• True out-of-time and out-of-sample test.
• Overall fitting is good in out-of-sample test
• Missed the refi wave in second half of 2016
MODEL RISK FACTORS

- **FICO**
  - Pre-2008
  - Post-2008
  - Actual vs. NNM

- **Current Loan Size**
  - Actual vs. NNM

- **CLTV**
  - Actual vs. NNM

- **SATO**
  - Actual vs. NNM
NNM and actual prepayment speeds against average incentive in prior 20 months
NNM and Hmodel Error Tracking against State Variables

NNM accurately captured state-level prepayment behaviors
Ranking- Based Sample Error Tracking for Coupon 4s

- Ranking based error tracking methodology provides a comprehensive measure of model accuracy across all pool variables
- NNM performed better than Hmodel
Sample ranking-based error tracking at different time point
NNM is able to pick up the general trend of HARP effectiveness but missed the complexity of its revolution.
MODEL SENSITIVITY

Model prepayment sensitivity to loan sizes and refinance Incentives

NNM captured the prepayment behavior for loan size

CPR vs Incentive (bps)

CPR vs Loan Size

75k 100k 150k 200k 300k 400k 500k

60 bps (LHS) -60 bps (RHS)
## “MEDIA EFFECT”

<table>
<thead>
<tr>
<th>Cohort</th>
<th>Observation Range</th>
<th>CPR</th>
<th>WALA</th>
<th>SATO</th>
<th>CLTV</th>
<th>CLNSZ</th>
<th>Incentive</th>
<th>FICO</th>
<th>Avg.UPB(bn)</th>
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<td>FH 3.5 2011</td>
<td>Jul.12 - Dec. 12</td>
<td>16.1</td>
<td>13</td>
<td>-5</td>
<td>77</td>
<td>212258</td>
<td>52</td>
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<td>15</td>
<td>3</td>
<td>78</td>
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<td>6.26</td>
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<td>21.9</td>
<td>12</td>
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<td>16</td>
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<td>29.2</td>
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<tr>
<td>FH 4 2010</td>
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<td>245496</td>
<td>44</td>
<td>767</td>
<td>23.02</td>
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</tbody>
</table>

2011 3.5s and 2010 4s prepayment speeds are compared across loan attributes, loan purpose and origination channel.

3.5s is much faster than 4s given similar loan attributes and incentive.
MODEL “MEDIA EFFECT”

2012 Vintage in 2012 refinance wave

2015 Vintage in 2016 refinance wave

CPR

Actual  NNM  Hmodel


3.5  4  4.5

CPR

Actual  NNM  Hmodel

Jan-16  May-16  Sep-16  Jan-17  May-17  Sep-17  Jan-18  Apr-16  Aug-16  Dec-16  Apr-17  Aug-17  Dec-17  Apr-18  Mar-16  Jul-16  Nov-16  Mar-17  Jul-17  Nov-17  Mar-18

3.5  4  4.5
In-time
Out-of-sample
(1/2003-12/2015)

1. All attributes statistics are very close on July and August 2016 except CPR.
2. Risk driver is missing, i.e., media effect or regime change

Out-of-time
Out-of-sample
(1/2016-4/2018)
MODEL ERROR TRACKING

In-time
Out-of-sample
(1/2003-10/2016)

Out-of-time
Out-of-sample
(11/2016-4/2018)
In-time
Out-of-sample (1/2003-10/2016)

When Increase weights on
8/2016 – 10/2016 by 40 times
in training:
1. Better in the early stage of out-of-time test
2. Sacrifice other period.

Out-of-time
MODEL ERROR TRACKING

In-time
Out-of-sample
(1/2003-10/2017)

Out-of-time
Out-of-sample
(10/2017-4/2018)
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### Contact us

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<thead>
<tr>
<th>AMERICAS</th>
<th>EUROPE, MIDDLE EAST &amp; AFRICA</th>
<th>ASIA PACIFIC</th>
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</thead>
<tbody>
<tr>
<td>Americas</td>
<td>+1 888 588 4567 *</td>
<td>Cape Town</td>
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