

# Asian SWIFT method

Efficient wavelet-based valuation of arithmetic Asian options

Álvaro Leitao, Luis Ortiz-Gracia and Emma I. Wagner



**BGSMath**  
BARCELONA GRADUATE SCHOOL OF MATHEMATICS



UNIVERSITAT DE BARCELONA  
SCHOOL OF ECONOMICS

**TU**Delft

CMMSE 2018 - Rota

July 10, 2018

# Motivation

- Arithmetic Asian options are still attractive in financial markets, but its numerical treatment is rather challenging.
- The valuation methods relying on Fourier inversion are highly appreciated, particularly for calibration purposes, since they are extremely fast, very accurate and easy to implement.
- Lack of robustness in the existing methods (number of terms in the expansion, numerical quadratures, truncation, etc.).
- The use of wavelets for other option problems (Europeans, early-exercise, etc.) has resulted in significant improvements in this sense.
- In the context of arithmetic Asian options, SWIFT provides extra benefits.

# Outline

- 1 Problem formulation
- 2 The SWIFT method
- 3 SWIFT for Asian options
- 4 Numerical results
- 5 Conclusions

# Problem formulation

- In Asian derivatives, the option payoff function relies on some *average* of the underlying values at a prescribed monitoring dates.
- Thus, the final value is less volatile and the option price cheaper.
- Consider  $N + 1$  monitoring dates  $t_i \in [0, T], i = 0, \dots, N$ .
- Where  $T$  is the maturity and  $\Delta t := t_{i+1} - t_i, \forall i$  (equal-spaced).
- Assume the initial state of the price process to be known,  $S(0) = S_0$ .
- Let averaged price be defined as  $A_N := \frac{1}{N+1} \sum_{i=0}^N S(t_i)$ , the payoff of the *European-style* Asian call option is

$$v(S, T) = (A_N - K)^+.$$

- The risk-neutral option valuation formula,

$$v(x, t) = e^{-r(T-t)} \mathbb{E} [v(y, T) | x] = e^{-r(T-t)} \int_{\mathbb{R}} v(y, T) f(y|x) dy,$$

with  $r$  the risk-free rate,  $T$  the maturity,  $f(y|x)$  the transitional density, typically unknown, and  $v(y, T)$  the payoff function.

# The SWIFT method

- A structure for wavelets in  $L^2(\mathbb{R})$  is called a *multi-resolution analysis*.
- We start with a family of closed nested subspaces in  $L^2(\mathbb{R})$ ,

$$\dots \subset \mathcal{V}_{-1} \subset \mathcal{V}_0 \subset \mathcal{V}_1 \subset \dots, \quad \bigcap_{m \in \mathbb{Z}} \mathcal{V}_m = \{0\}, \quad \overline{\bigcup_{m \in \mathbb{Z}} \mathcal{V}_m} = L^2(\mathbb{R}),$$

where

$$f(x) \in \mathcal{V}_m \iff f(2x) \in \mathcal{V}_{m+1}.$$

- Then, it exists a function  $\varphi \in \mathcal{V}_0$  generating an orthonormal basis, denoted by  $\{\varphi_{m,k}\}_{k \in \mathbb{Z}}$ , for each  $\mathcal{V}_m$ ,  $\varphi_{m,k}(x) = 2^{m/2} \varphi(2^m x - k)$ .
- The function  $\varphi$  is called the *scaling function* or *father wavelet*.
- For any  $f \in L^2(\mathbb{R})$ , a projection map of  $L^2(\mathbb{R})$  onto  $\mathcal{V}_m$ , denoted by  $\mathcal{P}_m : L^2(\mathbb{R}) \rightarrow \mathcal{V}_m$ , is defined by means of

$$\mathcal{P}_m f(x) = \sum_{k \in \mathbb{Z}} c_{m,k} \varphi_{m,k}(x), \quad \text{with} \quad c_{m,k} = \langle f, \varphi_{m,k} \rangle.$$

# The SWIFT method

- In this work, we employ Shannon wavelets. A set of Shannon scaling functions  $\varphi_{m,k}$  in the subspace  $\mathcal{V}_m$  is defined as,

$$\varphi_{m,k}(x) = 2^{m/2} \frac{\sin(\pi(2^m x - k))}{\pi(2^m x - k)} = 2^{m/2} \varphi(2^m x - k), \quad k \in \mathbb{Z},$$

where  $\varphi(z) = \text{sinc}(z)$ , with sinc the cardinal sine function.

- Given a function  $f \in L^2(\mathbb{R})$ , we will consider its expansion in terms of Shannon scaling functions at the level of resolution  $m$ .
- Our aim is to recover the coefficients  $c_{m,k}$  of this approximation from the Fourier transform of the function  $f$ , denoted by  $\hat{f}$ , defined as

$$\hat{f}(\xi) = \int_{\mathbb{R}} e^{-i\xi x} f(x) dx,$$

where  $i$  is the imaginary unit.

# The SWIFT method

- Following wavelets theory, a function  $f \in L^2(\mathbb{R})$  can be approximated at the level of resolution  $m$  by,

$$f(x) \approx \mathcal{P}_m f(x) = \sum_{k \in \mathbb{Z}} c_{m,k} \varphi_{m,k}(x),$$

where  $\mathcal{P}_m f$  converges to  $f$  in  $L^2(\mathbb{R})$ , i.e.  $\|f - \mathcal{P}_m f\|_2 \rightarrow 0$ , when  $m \rightarrow +\infty$ .

- The infinite series is well-approximated (see Lemma 1 of [2]) by a finite summation,

$$\mathcal{P}_m f(x) \approx f_m(x) := \sum_{k=k_1}^{k_2} c_{m,k} \varphi_{m,k}(x),$$

for certain accurately chosen values  $k_1$  and  $k_2$ .

# The SWIFT method

- Computation of the coefficients  $c_{m,k}$ : by definition,

$$c_{m,k} = \langle f, \varphi_{m,k} \rangle = \int_{\mathbb{R}} f(x) \bar{\varphi}_{m,k}(x) dx = 2^{m/2} \int_{\mathbb{R}} f(x) \varphi(2^m x - k) dx.$$

- Using the classical Vieta's formula truncated with  $2^{J-1}$  terms, the cosine product-to-sum identity and the definition of the characteristic function, the coefficients,  $c_{m,k}$ , can be approximated by

$$c_{m,k} \approx \frac{2^{m/2}}{2^{J-1}} \sum_{j=1}^{2^{J-1}} \Re \left[ \hat{f} \left( \frac{(2j-1)\pi 2^m}{2^J} \right) e^{\frac{ik\pi(2j-1)}{2^J}} \right].$$

- Putting everything together gives the following approximation of  $f$

$$f(x) \approx \sum_{k=k_1}^{k_2} c_{m,k} \varphi_{m,k}(x).$$



# SWIFT option valuation formulas

- Truncating the integration range on  $[a, b]$  and replacing density  $f$  by the SWIFT approximation,

$$v(x, t_0) \approx e^{-rT} \sum_{k=k_1}^{k_2} c_{m,k} V_{m,k},$$

where,

$$V_{m,k} := \int_a^b v(y, T) \varphi_{m,k}(y|x) dy.$$

- By employing the Vieta's formula again and interchanging summation and integration operations, we obtain that

$$V_{m,k} \approx \frac{2^{m/2}}{2^{J-1}} \sum_{j=1}^{2^{J-1}} \int_a^b v(y, T) \cos\left(\frac{2j-1}{2^J} \pi (2^m y - k)\right) dy.$$

# SWIFT for Asian options under exponential Lévy models

- Exponential Lévy models:  $\log S(t)$ , follows a Lévy process.
- The Lévy dynamics have a stationary and i.i.d. increments, fully described from its characteristic function.
- But, for arithmetic Asian options, the derivation of the corresponding characteristic function is rather involved.
- Lets start by defining the *return* or *increment* process  $R_i$ ,

$$R_i := \log \left( \frac{S(t_i)}{S(t_{i-1})} \right) \quad i = 1, \dots, N.$$

- Based on  $R_i$ , we define a new process

$$Y_i := R_{N+1-i} + Z_{i-1}, \quad i = 2, \dots, N,$$

where  $Y_1 = R_N$  and  $Z_i := \log(1 + e^{Y_i})$ ,  $\forall i$ .

# SWIFT for Asian options under exponential Lévy models

- Applying the Carverhill-Clewlow-Hodges factorization to  $Y_i$ ,

$$\frac{1}{N+1} \sum_{i=0}^N S(t_i) = \frac{(1 + e^{Y_N}) S_0}{N+1}.$$

- Thus, the option price for arithmetic Asian contracts can be now expressed in terms of the transitional density of the  $Y_N$  as

$$v(x, t_0) = e^{-rT} \int_{\mathbb{R}} v(y, T) f_{Y_N}(y) dy,$$

where  $x = \log S_0$  and the call payoff function is given by

$$v(y, T) = \left( \frac{S_0 (1 + e^y)}{N+1} - K \right)^+$$

- Again, the probability density function  $f_{Y_N}$  is generally not known, even for Lévy processes. However, as the process  $Y_N$  is defined in a recursive manner, the characteristic function of  $Y_N$  can be computed iteratively as well.

# Characteristic function of $Y_N$

- By the definition of  $Y_i$ , the initial and recursive characteristic functions are

$$\hat{f}_{Y_1}(\xi) = \hat{f}_{R_N}(\xi) = \hat{f}_R(\xi),$$

$$\hat{f}_{Y_i}(\xi) = \hat{f}_{R_{N+1-i} + Z_{i-1}}(\xi) = \hat{f}_{R_{N+1-i}}(\xi) \cdot \hat{f}_{Z_{i-1}}(\xi) = \hat{f}_R(\xi) \cdot \hat{f}_{Z_{i-1}}(\xi).$$

- By definition, the characteristic function of  $Z_{i-1}$  reads

$$\hat{f}_{Z_{i-1}}(\xi) := \mathbb{E} \left[ e^{-i\xi \log(1+e^{Y_{i-1}})} \right] = \int_{\mathbb{R}} (1+e^x)^{-i\xi} f_{Y_{i-1}}(x) dx.$$

- We can again apply the wavelet approximation to  $f_{Y_{i-1}}$  as

$$\begin{aligned} \hat{f}_{Z_{i-1}}(\xi) &\approx \int_{\mathbb{R}} (1+e^x)^{-i\xi} \sum_{k=k_1}^{k_2} c_{m,k} \varphi_{m,k}(x) dx \\ &= 2^{\frac{m}{2}} \sum_{k=k_1}^{k_2} c_{m,k} \int_{\mathbb{R}} (e^x + 1)^{-i\xi} \text{sinc}(2^m x - k) dx. \end{aligned}$$

# Characteristic function of $Y_N$

- The integral on the right hand side needs to be computed efficiently to make the method easily implementable, robust and very fast.
- State-of-the-art methods from the literature rely on solving the integral by means of quadratures.

## Theorem (Theorem 1.3.2 of [3])

Let  $f$  be defined on  $\mathbb{R}$  and let its Fourier transform  $\hat{f}$  be such that for some positive constant  $d$ ,  $|\hat{f}(\omega)| = \mathcal{O}(e^{-d|\omega|})$  for  $\omega \rightarrow \pm\infty$ , then as  $h \rightarrow 0$

$$\frac{1}{h} \int_{\mathbb{R}} f(x) S_{j,h}(x) dx - f(jh) = \mathcal{O}\left(e^{-\frac{\pi d}{h}}\right),$$

where  $S_{j,h}(x) = \text{sinc}\left(\frac{x}{h} - j\right)$  for  $j \in \mathbb{Z}$ .

- Theorem 1 allows us to approximate the integral above provided that  $g(x) := (e^x + 1)^{-i\xi}$  satisfies the hypothesis.

# Characteristic function of $Y_N$

- If we consider  $h = \frac{1}{2^m}$ , then it follows from Theorem 1 that

$$\int_{\mathbb{R}} g(x) \text{sinc}(2^m x - k) dx \approx hg(kh) = \frac{1}{2^m} \left( e^{\frac{k}{2^m}} + 1 \right)^{-i\xi}.$$

- Thus,  $\hat{f}_{Z_{i-1}}$  can be approximated by

$$\hat{f}_{Z_{i-1}}(\xi) \approx 2^{-\frac{m}{2}} \sum_{k=k_1}^{k_2} c_{m,k} \left( e^{\frac{k}{2^m}} + 1 \right)^{-i\xi}.$$

- Finally,

$$\hat{f}_{Y_i}(\xi) = \hat{f}_R(\xi) \hat{f}_{Z_{i-1}} \approx \hat{f}_R(\xi) 2^{-\frac{m}{2}} \sum_{k=k_1}^{k_2} c_{m,k} \left( e^{\frac{k}{2^m}} + 1 \right)^{-i\xi},$$

where the density coefficients  $c_{m,k}$  are computed as follows

$$c_{m,k} \approx \frac{2^{m/2}}{2^{J-1}} \sum_{j=0}^{2^{J-1}-1} \Re \left\{ \hat{f}_{Y_{i-1}} \left( \frac{(2j-1)\pi 2^m}{2^J} \right) e^{\frac{ik\pi(2j-1)}{2^J}} \right\}.$$

# Characteristic function of $Y_N$

- It remains to prove that function  $g(x) = (e^x + 1)^{-i\xi}$  satisfies  $|\hat{g}(\omega)| = \mathcal{O}(e^{-d|\omega|})$  for  $\omega \rightarrow \pm\infty$ .
- We have derived an expression for  $\hat{g}(\omega)$ ,

## Proposition

Let  $g(x) = (e^x + 1)^z$ , where  $z = -i\xi$  and  $x, \xi \in \mathbb{R}$ . Then,

$$\hat{g}(\omega) = \sum_{n=0}^{\infty} \binom{z}{n} \frac{2n - z}{(n - i\omega)(n + i(\omega + \xi))}, \quad \omega \in \mathbb{R}.$$

- It is rather complicated to get a closed-form solution for the modulus of  $\hat{g}(\omega)$  from this expression.

# Characteristic function of $Y_N$

- By employing Wolfram Mathematica 11.2, the infinite sum is written as

$$\hat{g}(\omega) = \frac{\xi}{2\omega + \xi} \left[ e^{-\pi\omega} (B_{-1}(-i\omega, 1+z) + 2B_{-1}(1-i\omega, z)) + \right. \\ \left. + \Gamma(i\omega - z) \left( {}_2\tilde{F}_1(1-z, 1+i\omega-z; 2+i\omega-z; -1) - {}_2\tilde{F}_1(-z, i\omega-z; 1+i\omega-z; -1) \right) \right],$$

in terms of gamma,  $\Gamma$ , beta,  $B$ , and regularized hypergeometric,  ${}_2\tilde{F}_1(a, b; c; \nu)$ .



# Characteristic function of $Y_N$

- Representing  $|\hat{g}(\omega)|$ ,

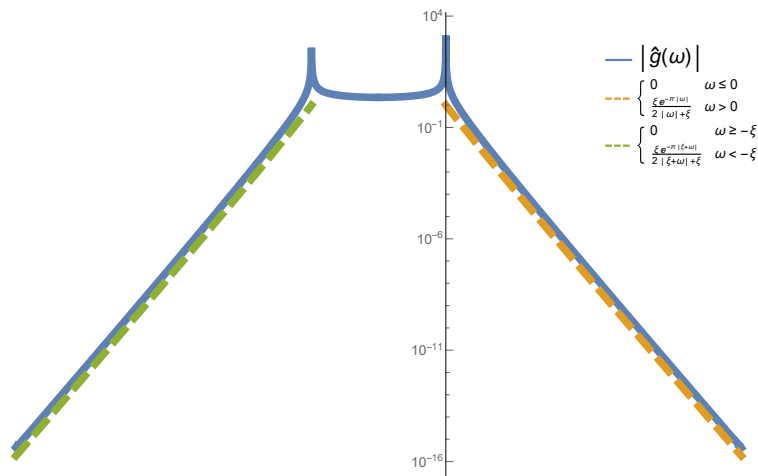


Figure: Modulus of  $\hat{g}(\omega)$ .

# Payoff coefficients

- To complete the SWIFT pricing formula, compute the payoff coefficients,  $V_{m,k}$ ,

$$V_{m,k} = \frac{2^{m/2}}{2^{J-1}} \sum_{j=1}^{2^{J-1}} \left[ \frac{S_0}{N+1} \left( l_2^{j,k}(\tilde{x}, b) + l_0^{j,k}(\tilde{x}, b) \right) - K l_0^{j,k}(\tilde{x}, b) \right],$$

where  $\tilde{x} = \log \left( \frac{K(N+1)}{S_0} - 1 \right)$  and the functions  $l_0^{j,k}$  and  $l_2^{j,k}$  are defined by the following integrals

$$l_0^{j,k}(x_1, x_2) := \int_{x_1}^{x_2} \cos(C_j(2^m y - k)) dy,$$

$$l_2^{j,k}(x_1, x_2) := \int_{x_1}^{x_2} e^y \cos(C_j(2^m y - k)) dy,$$

with  $C_j = \frac{2j-1}{2^J} \pi$ . These integrals are analytically available.

# Numerical results

- We compare the SWIFT method against a state-of-the-art method, the well-known COS method, particularly the COS variant for arithmetic Asian option, called ASCOS method [4].
- To the best of our knowledge, the ASCOS method provides the best balance between accuracy and efficiency.
- Arithmetic Asian call option valuation with varying number of monitoring dates,  $N = 12$  (monthly),  $N = 50$  (weekly) and  $N = 250$  (daily), and conceptually different underlying Lévy dynamics: *Geometric Brownian motion* (GBM) and *Normal inverse Gaussian* (NIG).
- We assess not only the accuracy in the solution but also the computational performance.
- All the experiments have been conducted in a computer system with the following characteristics: CPU Intel Core i7-4720HQ 2.6GHz and memory of 16GB RAM. The employed software package is Matlab R2017b.

# Results on GBM

| GBM                      |                      | $N = 12$                      | $N = 50$                       | $N = 250$                     |
|--------------------------|----------------------|-------------------------------|--------------------------------|-------------------------------|
|                          |                      | ASCOS                         |                                |                               |
| $N_c = 64, n_q = 100$    | Error<br>Time (sec.) | $3.75 \times 10^{-4}$<br>0.03 | $8.34 \times 10^{-4}$<br>0.02  | $7.17 \times 10^{-3}$<br>0.01 |
| $N_c = 128, n_q = 200$   | Error<br>Time (sec.) | $8.37 \times 10^{-7}$<br>0.03 | $7.43 \times 10^{-6}$<br>0.02  | $3.82 \times 10^{-5}$<br>0.02 |
| $N_c = 256, n_q = 400$   | Error<br>Time (sec.) | =<br>0.16                     | $5.33 \times 10^{-7}$<br>0.12  | $1.58 \times 10^{-7}$<br>0.11 |
| $N_c = 512, n_q = 800$   | Error<br>Time (sec.) | =<br>1.96                     | =<br>1.80                      | $3.04 \times 10^{-8}$<br>1.85 |
| $N_c = 1024, n_q = 1600$ | Error<br>Time (sec.) | =<br>13.99                    | =<br>13.99                     | =<br>14.25                    |
|                          |                      | SWIFT                         |                                |                               |
| $m = 4$                  | Error<br>Time (sec.) | $2.70 \times 10^{-4}$<br>0.01 | $1.27 \times 10^{-2}$<br>0.01  | $3.82 \times 10^{-2}$<br>0.03 |
| $m = 5$                  | Error<br>Time (sec.) | $7.47 \times 10^{-9}$<br>0.01 | $9.78 \times 10^{-5}$<br>0.02  | $4.01 \times 10^{-3}$<br>0.06 |
| $m = 6$                  | Error<br>Time (sec.) | =<br>0.02                     | $3.55 \times 10^{-10}$<br>0.10 | $6.96 \times 10^{-4}$<br>0.40 |
| $m = 7$                  | Error<br>Time (sec.) | =<br>0.08                     | =<br>0.34                      | $1.21 \times 10^{-8}$<br>1.37 |
| $m = 8$                  | Error<br>Time (sec.) | =<br>0.33                     | =<br>1.31                      | =<br>5.11                     |

**Table:** SWIFT vs. ASCOS. Setting: **GBM**,  $S_0 = 100$ ,  $r = 0.0367$ ,  $\sigma = 0.17801$ ,  $T = 1$  and  $K = 90$ . The reference values are 11.9049157487 ( $N = 12$ ), 11.9329382045 ( $N = 50$ ) and 11.9405631571 ( $N = 250$ ).

# Results on NIG

| NIG                      |                       | $N = 12$                      | $N = 50$                      | $N = 250$                     |
|--------------------------|-----------------------|-------------------------------|-------------------------------|-------------------------------|
| ASCOS                    |                       |                               |                               |                               |
| $N_c = 64, n_q = 100$    | Abs error<br>CPU time | $7.78 \times 10^{-3}$<br>0.03 | $1.71 \times 10^{-1}$<br>0.03 | $8.75 \times 10^{-2}$<br>0.02 |
| $N_c = 128, n_q = 200$   | Abs error<br>CPU time | $2.60 \times 10^{-4}$<br>0.03 | $5.89 \times 10^{-3}$<br>0.03 | $1.49 \times 10^{-2}$<br>0.03 |
| $N_c = 256, n_q = 400$   | Abs error<br>CPU time | =<br>0.19                     | =<br>0.17                     | $1.42 \times 10^{-4}$<br>0.15 |
| $N_c = 512, n_q = 800$   | Abs error<br>CPU time | =<br>1.98                     | =<br>1.96                     | =<br>2.02                     |
| $N_c = 1024, n_q = 1600$ | Abs error<br>CPU time | =<br>14.38                    | =<br>14.22                    | =<br>14.71                    |
| SWIFT                    |                       |                               |                               |                               |
| $m = 4$                  | Abs error<br>CPU time | $9.72 \times 10^{-2}$<br>0.02 | $9.27 \times 10^{-2}$<br>0.02 | $4.01 \times 10^{-2}$<br>0.04 |
| $m = 5$                  | Abs error<br>CPU time | $5.69 \times 10^{-3}$<br>0.02 | $6.92 \times 10^{-4}$<br>0.03 | $4.50 \times 10^{-3}$<br>0.08 |
| $m = 6$                  | Abs error<br>CPU time | $2.13 \times 10^{-4}$<br>0.02 | $9.12 \times 10^{-4}$<br>0.12 | $9.11 \times 10^{-4}$<br>0.48 |
| $m = 7$                  | Abs error<br>CPU time | =<br>0.13                     | =<br>0.47                     | =<br>1.52                     |
| $m = 8$                  | Abs error<br>CPU time | =<br>0.39                     | =<br>1.46                     | =<br>5.85                     |

**Table:** SWIFT vs. ASCOS. Setting: **NIG**,  $S_0 = 100$ ,  $r = 0.0367$ ,  $\sigma = 0.0$ ,  $\alpha = 6.1882$ ,  $\beta = -3.8941$ ,  $\delta = 0.1622$ ,  $T = 1$  and  $K = 110$ . The reference values are 1.0135 ( $N = 12$ ), 1.0377 ( $N = 50$ ) and 1.0444 ( $N = 250$ ).

# Conclusions

- A new Fourier inversion-based technique has been proposed in the framework of discretely monitored Asian options under exponential Lévy processes.
- The application of SWIFT to the Asian pricing problem allows to overcome the main drawbacks attributed to this type of methods.
- Specially, SWIFT allows to avoid the numerical integration in the recovery of the characteristic function.
- SWIFT results in a highly accurate and fast technique, outperforming the competitors in most of the analysed situations.

# References



Álvaro Leitaó, Luis Ortiz-Gracia, and Emma I. Wagner.

SWIFT valuation of discretely monitored arithmetic Asian options, 2018.

Available at SSRN: <https://ssrn.com/abstract=3124902>.



Luis Ortiz-Gracia and Cornelis W. Oosterlee.

A highly efficient Shannon wavelet inverse Fourier technique for pricing European options.

*SIAM Journal on Scientific Computing*, 38(1):118–143, 2016.



Frank Stenger.

*Handbook of Sinc numerical methods*.

CRC Press, Inc., Boca Raton, FL, USA, 2010.



Bowen Zhang and Cornelis W. Oosterlee.

Efficient pricing of European-style Asian options under exponential Lévy processes based on Fourier cosine expansions.

*SIAM Journal on Financial Mathematics*, 4(1):399–426, 2013.



Thanks to support from MDM-2014-0445

More: `leitao@ub.edu` and `alvaroleitao.github.io`

# Thank you for your attention



## Bonus - Proof expression $\hat{g}(\omega)$

### Proposition

Let  $z \in \mathbb{C}$  and  $\binom{z}{n} = \frac{z(z-1)(z-2)\cdots(z-n+1)}{n!}$ . Then the series  $\sum_{n=0}^{\infty} \binom{z}{n} x^n$  converges to  $(1+x)^z$  for all complex  $x$  with  $|x| < 1$ .

### Corollary

Let  $z \in \mathbb{C}$ . Then the series  $\sum_{n=0}^{\infty} \binom{z}{n} x^n y^{z-n}$  converges to  $(x+y)^z$  for all complex  $x, y$  with  $|x| < |y|$ .

### Proof.

The proof follows from Proposition by taking into account that

$$(x+y)^z = \left( y \left[ \frac{x}{y} + 1 \right] \right)^z.$$



## Bonus - Proof expression $\hat{g}(\omega)$

### Proof.

From the definition, we split the integral in two parts

$$\hat{g}(\omega) = \int_{\mathbb{R}} e^{-i\omega x} g(x) dx = \int_{-\infty}^0 e^{-i\omega x} g(x) dx + \int_0^{\infty} e^{-i\omega x} g(x) dx,$$

and observe that, by Corollary above,

$$(e^x + 1)^z = \sum_{n=0}^{\infty} \binom{z}{n} e^{nx}, \quad \text{for } x < 0, \quad \text{and} \quad (e^x + 1)^z = \sum_{n=0}^{\infty} \binom{z}{n} e^{(z-n)x}, \quad \text{for } x > 0.$$

Replacing expressions and interchanging the integral and the sum, then we obtain,

$$\hat{g}(\omega) = \sum_{n=0}^{\infty} \binom{z}{n} \int_{-\infty}^0 e^{-i\omega x} e^{nx} dx + \sum_{n=0}^{\infty} \binom{z}{n} \int_0^{\infty} e^{-i\omega x} e^{(z-n)x} dx.$$

Finally, solving the integrals,

$$\hat{g}(\omega) = \sum_{n=0}^{\infty} \binom{z}{n} \frac{1}{n - i\omega} + \sum_{n=0}^{\infty} \binom{z}{n} \frac{1}{n + i(\omega + \xi)} = \sum_{n=0}^{\infty} \binom{z}{n} \frac{2n - z}{(n - i\omega)(n + i(\omega + \xi))}.$$

